By<br>PAO-LIANG CHEN<br>Bachelor of Arts<br>National Chengchi University<br>Taipei, China<br>1965<br>\section*{Master of Science in Statistics San Diego State University San Diego, California 1973}

Submitted to the Faculty of the Graduate College of the Oklahoma State University
in partial fulfillment of the requirements for the Degree of
DOCTOR OF PHILOSOPHY
July, 1976

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ON THE JOINT DISTRIBUTION
OF COVERAGES

Thesis Approved:


964121

## ACKNOWLEDGEMENTS

I am grateful to Dr. David L. Weeks, my adviser, for suggesting the topic of this study and for his guidance all through the formulation of this thesis. I would like to thank Dr. William D. Warde, Dr. Ronald W. McNew and Dr. Rodger K. Johnson for serving on my committee. I owe Dr. Warde a debt of gratitude for his many useful suggestions.

I wish to express my sincere appreciation to Miss Me1ita Wyatt for her fine job in typing this manuscript and all my previous reports.

A special thanks goes to my wife, Feng-lai, whose help and understanding are invaluable to me.

## TABLE OF CONTENTS

Chapter Page
I. INTRODUCTION ..... 1

1. Statement of the Problem ..... 1
2. A Review of Previous Work ..... 3
3. The Order of Investigation ..... 4
II. THE DISTRIBUTION OF ONE LINEAR COVERAGE ..... 6
III. THE DISTRIBUTION OF ONE RECTANGULAR COVERAGE ..... 12
IV. THE JOINT C.D.F. OF TWO LINEAR COVERAGES AND ITS EXTENSION ..... 21
4. The Joint c.d.f. of Two Linear Coverages ..... 21
5. Some Extensions ..... 28
V. THE JOINT P.D.F. OF TWO LINEAR COVERAGES. ..... 30
VI. THE JOINT C.D.F. OF TWO RECTANGULAR COVERAGES ..... 43
6. An Attempt to Use the Joint p.d.f. of Two Linear Coverages ..... 43
7. An Alternative Approach ..... 45
VII. THE JOINT PROBABILITIES OF SOME INTERESTING EVENTS ..... 53
8. The Probability of Hitting Both Targets ..... 53
9. A Two-way Table to Find Probabilties of Some Other Interesting Events ..... 66
10. An Extension of the Two-way Table Method ..... 68
11. The Fewest Number of Passes Required to Achieve a Specified Probability of Hitting Both Targets ..... 71
12. The Probability of Achieving the Maximum Possible Coverage on Both Targets ..... 72
VIII. AN APPROXIMATION OF THE JOINT C.D.F. OF TWO RECTANGULAR COVERAGES ..... 78
IX. EXTENSION TO M RECTANGULAR TARGETS ..... 84
Chapter Page
X. SUMMARY AND POSSIBLE EXTENSIONS ..... 90
13. Summary ..... 90
14. Possible Extensions ..... 91
A SELECTED BIBLIOGRAPHY ..... 94
APPENDIX: A NUMERICAL EXAMPLE OF THE JOINT PROBABILITY OF TWO RECTANGULAR COVERAGES ..... 96

## LIST OF TABLES

Table ..... Page
I. Cases of $K_{1} \cap K_{2}$ ..... 59
II. The Exact Joint Probability of Two Fractional Coverages ..... 104
III. The Approximated Joint Probability of Two Fractional Coverages ..... 104

## LIST OF FIGURES

Figure Page

1. A Typical Situation ..... 1
2. A Linear Pattern Being Delivered on a Linear Target ..... 7
3. The Functional Relationship between C and Y ..... 8
4. The c.d.f. of One Linear Coverage ..... 9
5. The p.d.f. of One Linear Coverage ..... 10
6. The Joint p.d.f. of Linear Coverages in Range and Deflection Directions ..... 15
7. Using 'Distribution Function Method' to Obtain the c.d.f. of the Rectangular Coverage ..... 16
8. The p.d.f. of One Rectangular Coverage ..... 20
9. The Functional Relationship between $\mathrm{C}_{1}, \mathrm{C}_{2}$, and Y ..... 22
10. A Distribution Function of Two Linear Coverages ..... 27
11. When $u_{2}$ Increases Along the Interval $u_{1}=S_{1}-R_{1}$, $0<\mathrm{u}_{2}<\mathrm{S}_{2}-\mathrm{R}_{2}$ ..... 37
12. A p.d.f. of Two Linear Coverages. ..... 41
13. The Region Corresponding to the Event ( $Z \leq v$ ) ..... 46
14. The Region Corresponding to the Event $\left(Z_{1} \leq v_{1}\right.$, $z_{2} \leq v_{2}$ ) ..... 48
15. Some Possible Shapes $D_{1} \cap D_{2}$ May Take. ..... 51
16. The Rectang1e Corresponding to the Event "Hitting Target 1" ..... 54
17. The Rectangle Corresponding to the Event
'Hitting Both Targets" ..... 55
18. Types of Intersection of the Sets $K_{1}$ and $K_{2}$ ..... 56
Figure Page
19. Targets Overlapping Implied by Case 30 ..... 64
20. A Two-way Table of Joint Probabilities ..... 67
21. A Two-way Table with Numerical Values ..... 67
22. A Two-way Table for n Identical Patterns ..... 69
23. A Two-way Table for the ith Non-identical Pattern ..... 69
24. A Two-way Table for n Non-identical Patterns. ..... 70
25. The Region Corresponding to the Event 'Achieving MPC1' ..... 73
26. The Region Corresponding to the Event "Achieving MPC on Both Targets" ..... 75
27. Approximating $\mathrm{D}_{1}$ and $\mathrm{D}_{2}$ by Two Rectangles ..... 79
28. The Rectangle Corresponding to the Event 'Hitting A11 Three Targets" ..... 85
29. The Heart Is More Important than the Body ..... 91
30. An Example of One Rectangular Pattern Being Delivered on Two Rectangular Targets ..... 98
31. An Numerical Example of $D_{1} \cap D_{2}$ ..... 101

## CHAPTER I

## INTRODUCTION

## 1. Statement of the Problem

The problem which will be considered in this study is that of finding the joint distribution of the coverages of two rectangular targets by one rectangular pattern. To present the problem clearly, let us consider a typical situation which is exemplified by Figure 1 below:


Figure 1. A Typical Situation

In the diagram, $(0,0)$ and $(5,30)$ are the centers of Target 1 and Target 2 respectively. The sizes of the targets and the pattern are indicated beneath each of them. The aimpoint of the pattern is $(2,15)$. The coordinate system used here is range direction-deflection direction where the range direction is vertical and the deflection direction is horizontal.

The assumptions we make in regard to the general situation are:
(1) Both targets are rectangular in shape with sides of different target elements paralle1 to each other.
(2) The pattern is also rectangular in shape.
(3) Pattern sides are paralle1 to target sides.
(4) The landing point ( $\ell, \ell^{\prime}$ ) of the pattern center is assumed to have a bivariate normal distribution with correlation coefficient $\rho=0$. That is

$$
\begin{aligned}
& f\left(\ell, \ell^{\prime}\right)=\frac{1}{2 \pi \sigma \sigma^{\prime}} \exp \left\{-\frac{1}{2}\left[\left(\frac{\ell-\mathrm{M}}{\sigma}\right)^{2}\right.\right.\left.\left.+\left(\frac{\ell^{\prime}-\mathrm{M}^{\prime}}{\sigma^{\prime}}\right)^{2}\right]\right\} \\
&-\infty<y<\infty \\
&-\infty<y^{\prime}<\infty .
\end{aligned}
$$

where ( $M, M^{\prime}$ ) is the aimpoint of the pattern center point, and where $\sigma$ and $\sigma^{\prime}$ are the standard deviations of the landing point in the range and deflection directions respectively. Note that if we let $y=\frac{\ell}{\sigma}$, $y^{\prime}=\frac{\ell^{\prime}}{\sigma^{\prime}}, \quad \mu=\frac{M^{\prime}}{\sigma}$, and $\mu^{\prime}=\frac{M^{\prime}}{\sigma^{\prime}}$, then the joint p.d.f. of $y$ and $y^{\prime}$ is given by :

$$
\begin{array}{r}
f\left(y, y^{\prime}\right)=\frac{1}{2 \pi} \exp \left\{-\frac{1}{2}\left[(y-\mu)^{2}+\left(y^{\prime}-\mu^{\prime}\right)^{2}\right]\right\} \\
-\infty<y<\infty \\
-\infty<y^{\prime}<\infty . \tag{1.1}
\end{array}
$$

The question which prompts our study is: "Can we make any probability statements about the joint coverage on the two targets under this given situation?" More specifically:
(1) What is the probability of hitting both targets?
(2) What is the probability of hitting Target 1 but missing Target 2 ?
(3) What is the probability of hitting Target 2 but missing Target 1?
(4) What is the probability of missing both targets?
(5) What is the probability of achieving the maximum possible coverage on both targets?
(6) What is, say, $\operatorname{Pr}\left(z_{1} \geq 100\right.$ and $\left.z_{2} \geq 50\right)$ ? $\left(z_{1}\right.$ is the coverage on Target 1 and $z_{2}$ is the coverage on Target 2 by the pattern.)

## 2. A Review of Previous Work

Very little has been done on the subject of the joint distribution of two coverages (linear or rectangular). The majority of the earlier work in this field deals with the average value of coverages, e.g., the Expected Fractional Coverage. In the previous work, no probability statements are given with regard to coverage except in a study done by Gay and Weeks (1973). They derive the distribution function of the fractional coverage of one rectangular target by one rectangular pattern. A computer program using numerical integration was used to obtain the distribution function. A plotting program was also included.

The work by Gay and Weeks is by far the most relevant to our current study. Although it does not consider the joint probability of two rectangular coverages. Heiser (1971) also studied the distribution of
coverage on one rectangular target, but he allowed a free delivery angle of the rectangular pattern which made the coverage on the target non-rectangular in general.

In 'Matrix Evaluator Computer Program' (1974), a functional relationship between the linear coverage and the landing point of the pattern center was given. This relationship has proven to be very useful in our derivation of the joint distribution of two linear coverages.

## 3. The Order of Investigation

We shall first derive in Chapter II the cumulative distribution function (c.d.f.) and the probability density function (p.d.f.) of the coverage of one linear target by one linear pattern. In Chapter III, the c.d.f. and p.d.f. of the coverage of one rectangular target by one rectangular pattern is found. The approach we use in Chapter III is different from that used by Gay and Weeks. As a consequence, an equivalent but a somewhat more compact form of the c.d.f. is obtained.

In Chapters IV and V, we derive the joint c.d.f. and the joint p.d.f. of the coverages of two linear targets by one linear pattern.

It is in Chapter VI that the problem of the joint c.d.f. of two rectangular coverages is considered. In Section 1, of Chapter VI, we follow the line of approach used hitherto to obtain a 'mathematical expression" for the joint c.d.f., which turns out to be of little practical value. In Section 2, the approach used by Gay and Weeks is used to obtain another 'mathematical expression' for the joint c.d.f. of two rectangular coverages. Unfortunately, it is again untamed by attempts to computer program it. In both cases, we point out the difficulties and complexities involved in trying to program it.

In Chapter VII, we consider the joint probabilities of some "interesting" and "useful" cases. Namely, Question (1) through Question (5) stated in Section 1 of this chapter. Exact probabilities are obtained in closed forms in these cases.

In Chapter VIII, the problem of the joint c.d.f. of two rectangular coverages is picked up again. An approximation to it is given. Chapter IX outlines an easy way to extend this study to $m$ rectangular targets. In the final chapter, we give a summary and indicate some possible extensions.

## CHAPTER II

## THE DISTRIBUTION OF ONE LINEAR COVERAGE*

We start our investigation by considering the simplest case, that being one linear pattern delivered on one linear target. Let us adopt the following notation:

```
L
\beta = target center
L
M = aimpoint
\sigma = standard deviation of the landing point of the pattern center
                (aiming error)
T = L
0 = \beta/\sigma standardized target center
P = LP
\mu = M/\sigma standardized aimpoint.
```

Figure 2 illustrates the situation of one linear pattern being delivered on one linear target using the above notation.

[^0]
[ ] indicates the limits of the target
( ) indicates the limits of the pattern realization

Figure 2. A Linear Pattern Being Delivered on a Linear Target

In Figure 2, $y$ is the standardized landing point of the pattern center point, and according to the assumptions stated previously, y has a normal ( $\mu, 1$ ) distribution of the form

$$
\begin{equation*}
f(y)=\frac{1}{\sqrt{2 \pi}} \exp \left\{-\frac{1}{2}(y-\mu)^{2}\right\} \quad-\infty<y<\infty . \tag{2.1}
\end{equation*}
$$

Also, the shaded portion of the line in Figure 2 is the standardized linear coverage. Since all of the subsequent discussion will be in terms of standardized distances (being expressed in units of standard deviations), we shall drop the modifier "standardized" henceforth.

The functional relationship between $C$, the random variable which represents the linear coverage of the target, and $Y$, the random variable which represents the landing point of the pattern center is as follows: (This is a generalized version of what has been established in 'Matrix Evaluator Computer program" (1974, pp. 5-6),

$$
C=h(y)= \begin{cases}0 & \text { for } \quad y<-S+\theta  \tag{2.2}\\ S-\theta+y & \text { for }-S+\theta \leq y<-R+\theta \\ S-R & \text { for }-R+\theta \leq y<R+\theta \\ S+\theta-y & \text { for } \quad R+\theta \leq y<S+\theta \\ 0 & \text { for } \quad y \geq S+\theta\end{cases}
$$

where $S=T+P$ and $R=|T-P|$. The graph of this function is found in Figure 3.


Figure 3. The Functional Relationship between $C$ and $Y$

We note in Figure 3 that the maximum that the coverage $C$ can attain is $S-R$, which is the minimum of 2 T and 2 P .

We can now obtain the c.d.f. of $C$ by integrating $f(y)$, which is defined in (2.1), over the proper intervals indicated in Figure 3, corresponding to various values of $u$. This yields the following c.d.f.:

$$
F_{C}(u)= \begin{cases}0 & \text { for } u<0  \tag{2.3}\\ G(u-S+\theta-\mu)+G(u-S-\theta+\mu) & \text { for } 0 \leq u<S-R \\ 1 & \text { for } u \geq S-R\end{cases}
$$

where $G(\cdot)$ is the cumulative standard normal distribution function, and $u$ is a standardized value. Figure 4 is a plot of $F_{C}(u)$ :


Figure 4, The c.d.f. of One Linear Coverage

The p.d.f. of C is then

$$
f_{C}(u)= \begin{cases}0 & \text { for } u<0  \tag{2.4}\\ G(-S+\theta-\mu)+G(-S-\theta+\mu) & \text { for } u=0 \\ g(u-S+\theta-\mu)+g(u-S-\theta+\mu) & \text { for } 0<u<S-R \\ 1-G(-R+\theta-\mu)-G(-R-\theta+\mu) & \text { for } u=S-R \\ 0 & \text { for } u>S-R\end{cases}
$$

where $g(\cdot)$ is the standard normal density function.
Figure 5 below is a graph of $f_{C}(u)$ :


Figure 5. The p.d.f. of One Linear Coverage

To conclude, we have derived the c.d.f. and the p.d.f. of one linear coverage in Formulas (2.3) and (2.4). We note that this random variable is neither continuous nor discrete, but a mixture of both.

## CHAPTER III

THE DISTRIBUTION OF ONE RECTANGULAR COVERAGE

In this chapter, we shall consider the distribution of one rectangular coverage instead of one linear coverage which was treated in Chapter II.

First we shall obtain the joint p.d.f. of $C$ and $C^{\prime}$, the linear coverages in the range direction and the deflection direction respectively. Once the joint p.d.f. of $C$ and $C^{\prime}$ is obtained, we can find the c.d.f. of the rectangular coverage $Z$, by noting the fact that $Z=C \cdot C$ ' and accordingly using the so called 'Distribution Function Method.'"* We now proceed to do exactly that.

If we consider the notation defined above, i.e., $L_{T}, \beta, L_{p}, \mu$, etc. as being in the range direction, then expression (2.4) can be considered as the p.d.f. of $C$, the linear coverage in the range direction. Now if we use the same notation with a prime added to each of them to denote the same thing in the deflection direction, then the p.d.f. of $\mathrm{C}^{\prime}$, the linear coverage in the deflection direction, can be similarly obtained as:

[^1]\[

f_{C^{\prime}}\left(u^{\prime}\right)= $$
\begin{cases}0 & \text { for } u^{\prime}<0  \tag{3.1}\\ G\left(-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+G\left(-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right) & \text { for } u^{\prime}=0 \\ g\left(u^{\prime}-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+g\left(u^{\prime}-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right) & \text { for } 0<u^{\prime}<S^{\prime}-R^{\prime} \\ 1-G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right) & \text { for } u^{\prime}=S^{\prime}-R^{\prime} \\ 0 & \text { for } u^{\prime}>S^{\prime}-R^{\prime} .\end{cases}
$$
\]

Now the joint p.d.f. of $C$ and $C^{\prime}$ is simply the product of $f_{C}(u)$ and $f_{C^{\prime}}\left(u^{\prime}\right)$. This is due to the fact that $Y$ and $Y^{\prime}$ were assumed to be independent, that $C$ is a function of $Y$ only, and that $C^{\prime}$ is a function of $Y^{\prime}$ only. It is given as follows on next page:

$$
\begin{align*}
& \left\{\begin{array}{l}
0 \quad \text { for } u<0, \text { or } u>S-R, \text { or } u^{\prime}<0, \text { or } u^{\prime}>S^{\prime}-R \\
{[G(-S+\theta-\mu)+G(-S-\theta+\mu)] \cdot\left[G\left(-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+G\left(-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]} \\
\text { for } u=0 \text { and } u^{\prime}=0 \\
{[G(-S+\theta-\mu)+G(-S-\theta+\mu)] \cdot\left[g\left(u^{\prime}-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+g\left(u^{\prime}-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]}
\end{array}\right. \\
& \text { for } u=0 \text { and } 0<u^{\prime}<S^{\prime}-R^{\prime} \\
& {[G(-S+\theta-\mu)+G(-S-\theta+\mu)] \cdot\left[1-G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]} \\
& \text { for } u=0 \text { and } u^{\prime}=S^{\prime}-R^{\prime} \\
& {[g(u-S+\theta-\mu)+g(u-S-\theta+\mu)] \cdot\left[G\left(-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+G\left(-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]} \\
& \text { for } 0<u<S-R \text { and } u^{\prime}=0 \\
& f_{C, C},\left(u, u^{\prime}\right)=\left\{[g(u-S+\theta-\mu)+g(u-S-\theta+\mu)] \cdot\left[g\left(u^{\prime}-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+g\left(u^{\prime}-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right] .\right. \\
& \text { for } 0<u<S-R \text { and } 0<u^{\prime}<S^{\prime}-R^{\prime} \\
& {[g(u-S+\theta-\mu)+g(u-S-\theta+\mu)] \cdot\left[1-G\left(-P^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(-P^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]} \\
& \text { for } 0<u<S-P \text { and } u=S^{\prime}-P^{\prime} \\
& {[1-G(-R+\theta-\mu)-G(-R-\theta+\mu)] \cdot\left[G\left(-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+G\left(-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]} \\
& \text { for } u=S-R \text { and } u^{\prime}=0 \\
& {[1-G(-R+\theta-\mu)-G(-R-\theta+\mu)] \cdot\left[g\left(u^{\prime}-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+g\left(u^{\prime}-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]} \\
& \text { for } u=S-R \text { and } 0<u^{\prime}<S^{\prime}-R^{\prime} \\
& {[1-G(-R+\theta-\mu)-G(-R-\theta+\mu)] \cdot\left[1-G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]} \\
& \text { for } u=S-R \text { and } u^{\prime}=S^{\prime}-R^{\prime} . \tag{3.2}
\end{align*}
$$

Again this is an example of a "mixed" p.d.f. This means that the probability mass of this p.d.f. is concentrated on four points, areas on four "walls" and the volume in the middle. This is illustrated by the graph of $f_{C, C},\left(u, u^{\prime}\right)$ in Figure 6:


Figure 6. The Joint p.d.f. of Linear Coverages in Range and Deflection Directions

If we sum up the functional values of the four points $(0,0),\left(0, S^{\prime}-R^{\prime}\right)$, $(S-R, 0),(S-R, S '-R ')$, and areas of the four "walls" whose base lines are $\left\{\left(u, u^{\prime}\right) \mid u=0,0<u^{\prime}<S^{\prime}-R^{\prime}\right\},\left\{\left(u, u^{\prime}\right) \mid u=S-R, 0<u^{\prime}<S^{\prime}-R^{\prime}\right\}$, $\left\{\left(u, u^{\prime}\right) \mid 0<u<S-R, u^{\prime}=0\right\},\left\{\left(u, u^{\prime}\right) \mid 0<u<S-R, u^{\prime}=S^{\prime}-R^{\prime}\right\}$, and the volume whose base is $\left\{\left(u, u^{\prime}\right) \mid 0<u<S-R, 0<u^{\prime}<S^{\prime}-R^{\prime}\right\}$ in the diagram on Figure 6, we shall get one, the whole probability mass of this joint p.d.f.

Once the joint p.d.f. of C and $\mathrm{C}^{\prime}$ is obtained in (3.2), we can derive the c.d.f. of the rectangular coverage, $z=C \cdot C^{\prime}$, by using the "Distribution Function Method." In applying this method here we simply realize that $\operatorname{Pr}(Z \leq v)=\operatorname{Pr}\left(C \cdot C^{\prime} \leq v\right)$ which can be found for any specified $v$ value by first summing over the probability mass of the points, areas, and volume whose "base" is inside the lower right corner in Figure 7, and then to subtract this sum from one. (Note that the value $v$ has been standardized.)


Figure 7. Using 'Distribution Function Method" to Obtain the c.d.f. of the Rectangular Coverage

Now let us carry this out.

$$
\begin{aligned}
& \text { For } v<0, \operatorname{Pr}(Z \leq v)=0 . \\
& \text { For } v \geq(S-R)\left(S^{\prime}-R^{\prime}\right), \operatorname{Pr}(Z \leq v)=1 . \\
& \text { For } 0 \leq v<(S-R)\left(S^{\prime}-R^{\prime}\right), \\
& \operatorname{Pr}(Z \leq v) \\
& =1-\left\{[1-G(-R+\theta-\mu)-G(-R-\theta+\mu)] \cdot\left[1-G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]\right. \\
& \quad+\int_{v /\left(S^{\prime}-R R^{\prime}\right)}^{S-R}[g(u-S+\theta-\mu)+g(u-S-\theta+\mu)] \cdot\left[1-G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right] d u \\
& \quad+\int_{v /(S-R)}^{S^{\prime}-R^{\prime}}
\end{aligned}
$$

$$
\left.+\int_{v / S-R)}^{S^{\prime}-R^{\prime}} \int_{v / u^{\prime}}^{S-R}[g(u-S+\theta-\mu)+g(u-S-\theta+\mu)] \cdot\left[g\left(u^{\prime}-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+g\left(u^{\prime}-S^{\prime}-\theta^{\prime}+\mu\right)\right] d u d u^{\prime}\right\}
$$

$$
=1-\left\{[1-G(-R+\theta-\mu)-G(-R-\theta+\mu)] \cdot\left[1-G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]\right.
$$

$$
+\left[1-G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right] \cdot\left[G(-R+\theta-\mu)-G\left(V /\left(S^{\prime}-R^{\prime}\right)-S+\theta-\mu\right)\right.
$$

$$
\left.+G(-R-\theta+\mu)-G\left(V /\left(S^{\prime}-R^{\prime}\right)-S-\theta+\mu\right)\right]
$$

$$
+[1-G(-R+\theta-\mu)-G(-R-\theta+\mu)] \cdot\left[G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(V /(S-R)-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)\right.
$$

$$
\left.+G\left[-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right)-G\left(V /(S-R)-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]
$$

$$
+[G(-R+\theta-\mu)+G(-R-\theta+\mu)] \cdot\left[G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(V /(S-R)-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)\right.
$$

$$
\left.+G\left(-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right)-G\left(v /(S-R)-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]
$$

$$
\left.-\int_{v / S-R)}^{S^{\prime}-R^{\prime}}\left[g\left(u^{\prime}-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+g\left(u^{\prime}-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right] \cdot\left[G\left(v / u^{\prime}-S+\theta-\mu\right)+G\left(v / u^{\prime}-S-\theta+\mu\right)\right] d u^{\prime}\right\}
$$

$$
\begin{aligned}
& =\left[G\left(v /\left(S^{\prime}-R^{\prime}\right)-S+\theta-\mu\right)+G\left(v /\left(S^{\prime}-R^{\prime}\right)-S-\theta+\mu\right)\right] \cdot\left[1-G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-C_{1}\left(-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right] \\
& +G\left(v /(S-R)-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+G\left(v /(S-R)-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right) \\
& +\int_{v /(S-R)}^{S^{\prime}-R^{\prime}}\left[g\left(u^{\prime}-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+g\left(u^{\prime}-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right] \cdot\left[G\left(v / u^{\prime}-S+\theta-\mu\right)+G\left(v / u^{\prime}-S-\theta+\mu\right)\right] d u^{\prime}
\end{aligned}
$$

To summarize, we have the following c.d.f. of the rectangular coverage, $Z:$

$$
F_{Z}(v)=\left\{\begin{array}{l}
0 \quad \text { for } \quad v<0  \tag{3.3}\\
{\left[G\left(v /\left(S^{\prime}-R^{\prime}\right)-S+\theta-\mu\right)+G\left(v /\left(S^{\prime}-R^{\prime}\right)-S-\theta+\mu\right)\right]} \\
{\left[1-G\left(-R^{\prime}+\theta^{\prime}-\mu^{\prime}\right)-G\left(-R^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right]} \\
+G\left(v /(S-R)-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+G\left(v /(S-R)-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right) \\
+\int_{v /(S-R)}^{S^{\prime}-R^{\prime}}\left[g\left(u^{\prime}-S^{\prime}+\theta^{\prime}-\mu^{\prime}\right)+g\left(u^{\prime}-S^{\prime}-\theta^{\prime}+\mu^{\prime}\right)\right] \\
{\left[G\left(v / u^{\prime}-S+\theta-\mu\right)+G\left(v / u^{\prime}-S-\theta+\mu\right)\right] d u^{\prime}} \\
1 \\
\text { for } 0 \leq v<(S-R)\left(S^{\prime}-R R^{\prime}\right) \\
\text { for } v \geq(S-R)\left(S^{\prime}-R^{\prime}\right)
\end{array}\right.
$$

We must give a warning immediately. When $v=0$, the term $v / u^{\prime}$ in expression (3.3) must be defined to be 0 . Otherwise, $v / u^{\prime}$ is undefined at the lower limit of the integration when $v=0$.

The approach we used here to derive $\mathrm{F}_{Z}(\mathrm{v})$ in (3.3) is entirely different from that used by Gay and Weeks (1973). It is interesting to note that when we assume the target center $\left(\theta, \theta^{\prime}\right)=(0,0)$ and the aimpoint $\left(\mu, \mu^{\prime}\right)=(0,0)$, expression (3.3) will reduce to expression (3.4) below, which is equivalent to the c.d.f. found in Gay and Weeks (1973, pp. 20-21) except that we have a more compact and unified form here, ie.,

$$
F_{Z}(v)=\left\{\begin{array}{lc}
0 & \text { for } v<0  \tag{3.4}\\
{\left[2 G\left(v /\left(S^{\prime}-R^{\prime}\right)-S\right)\right] \cdot\left[1-2 G\left(-R^{\prime}\right)\right]+2 G\left(v /(S-R)-S^{\prime}\right)} \\
+\int_{v /(S-R)}^{S^{\prime}-R^{\prime}} 4 g\left(u^{\prime}-S^{\prime}\right) G\left(v / u^{\prime}-S\right) d u^{\prime} & \text { for } 0 \leq v<(S-R)\left(S^{\prime}-R^{\prime}\right) \\
1 & \text { for } v \geq(S-R)\left(S^{\prime}-R^{\prime}\right)
\end{array}\right.
$$

The p.d.f. of $z$, the rectangular coverage, is derived by taking derivatives of (3.3) and taking account of the "jumps" at $v=0$ and $v=(S-R)\left(S^{\prime}-R^{\prime}\right)$. Leibnitz Rule is used in this differentiation. After simplification, we obtain:

A graph of $f_{z}(v)$ is as given in Figure 8.


Figure 8. The p.d.f. of One Rectangular Coverage

In this chapter, we have derived both the c.d.f. and the p.d.f. of one rectangular coverage. In the next two chapters we shall develop the joint distribution, i.e., the joint c.d.f. and the joint p.d.f. of two linear coverages.

## CHAPTER IV

## THE JOINT C.D.F. OF TWO LINEAR COVERAGES

AND ITS EXTENSION

## 1. The Joint c.d.f. of Two Linear Coverages

We shall make use of the same notation defined in Chapter II with subscript " 1 " or " 2 " added to $\mathrm{L}_{\mathrm{T}}, \beta, \mathrm{T}, \theta, \mathrm{S}$, and R to differentiate between Target 1 and Target 2 .

Suppose we have two linear targets. Target 1 has 1 ength $2 \mathrm{~T}_{1}$ with center at $\theta_{1}=2$. Target 2 has length $2 \mathrm{~T}_{2}$ with center at $\theta_{2}$. (Let us adopt the convention that we always denote the target on the left as Target 1 and assign zero as the coordinate of its center). A linear pattern of length 2 P aimed at point $\mu$ is delivered on them. The distribution of $Y$, the landing point of the pattern center is assumed to be normal ( $\mu, 1$ ) as before.

The linear coverage of Target $1, \mathrm{C}_{1}$, is again a function of Y . So is $C_{2}$, the linear coverage of Target 2 . That is:
$C_{1}=h_{1}(y)=\left\{\begin{array}{lll}0 & \text { for } & y \leq-S_{1} \\ S_{1}+y & \text { for } & -S_{1}<y<-R_{1} \\ S_{1}-R_{1} & \text { for } & -R_{1} \leq y \leq R_{1} \\ S_{1}-y & \text { for } & R_{1}<y<S_{1} \\ 0 & \text { for } & y \geq S_{1}\end{array}\right.$
and
$C_{2}=h_{2}(y)= \begin{cases}0 & \text { for } y \leq-S_{2}+\theta 2 \\ S_{2}-\theta_{2}+y & \text { for }-S_{2}+\theta_{2}<y--R_{2}+\theta 2 \\ S_{2}-R_{2} & \text { for }-R_{2}+\theta_{2} \leq y \leq R_{2}+() 2 \\ S_{2}+\theta_{2}-y & \text { for } R_{2}+\theta_{2}<y<S_{2}+\theta 2 \\ 0 & \text { for } y \geq S+\theta_{2} .\end{cases}$
These two functions, (4.1) and (4.2), can be graphed on the same axis. One possible configuration of targets and pattern is shown on the diagram in Figure 9. We note again the maximum that the coverage $\mathrm{C}_{1}$ can attain is

$$
\mathrm{S}_{1}-\mathrm{R}_{1}=\min \left(2 \mathrm{~T}_{1}, 2 \mathrm{P}\right)
$$

and the maximum that the coverage $C_{2}$ can attain is

$$
\mathrm{S}_{2}-\mathrm{R}_{2}=\min \left(2 \mathrm{~T}_{2}, 2 \mathrm{P}\right)
$$



Figure 9. The Functional Re1ationship between $\mathrm{C}_{1}, \mathrm{C}_{2}$, and Y

Now let us proceed to find the joint c.d.f. of $C_{1}$ and $C_{2}$, namely, $\mathrm{F}_{\mathrm{C}_{1}, \mathrm{C}_{2}}\left(\mathrm{u}_{1}, \mathrm{u}_{2}\right)=\operatorname{Pr}\left(\mathrm{C}_{1} \leq \mathrm{u}_{1}, \mathrm{C}_{2} \leq \mathrm{u}_{2}\right)$. Since $\operatorname{Pr}\left(\mathrm{C}_{1} \leq \mathrm{u}_{1}, \mathrm{C}_{2} \leq \mathrm{u}_{2}\right)$ will have different expressions, corresponding to the possible values $u_{1}$ and $\mathrm{u}_{2}$ may assume, we first break the $\mathrm{U}_{1} \mathrm{U}_{2}$ plane into five disjoint regions:
(1) $\mathrm{u}_{1}<0$ or $\mathrm{u}_{2}<0$
(2) $u_{1} \geq S_{1}-R_{1}$ and $u_{2} \geq S_{2}-R_{2}$
(3) $\mathrm{u}_{1} \geq \mathrm{S}_{1}-\mathrm{R}_{1}$ and $0 \leq \mathrm{u}_{2}<\mathrm{S}_{2}-\mathrm{R}_{2}$
(4) $0 \leq u_{1}<S_{1}-R_{1}$ and $u_{2} \geq S_{2}-R_{2}$
(5) $0 \leq u_{1}<S_{1}-R_{1}$ and $0 \leq u_{2}<S_{2}-R_{2}$.

We can find the $\operatorname{Pr}\left(C_{1} \leq u_{1}, C_{2} \leq u_{2}\right)$ region by region as follows:

For Region (1): $u_{1}<0$ or $u_{2}<0$,

$$
\operatorname{Pr}\left(\mathrm{C}_{1} \leq \mathrm{u}_{1}, \mathrm{C}_{2} \leq \mathrm{u}_{2}\right)=0
$$

since coverages are non-negative.
For Region (2): $u_{1} \geq S_{1}-R_{1}$ and $u_{2} \geq S_{2}-R_{2}$,

$$
\operatorname{Pr}\left(\mathrm{C}_{1} \leq \mu_{1}, \mathrm{C}_{2} \leq \mathrm{u}_{2}\right)=1
$$

since $\left(\mathrm{S}_{1}-\mathrm{R}_{1}\right)$ and $\left(\mathrm{S}_{2}-\mathrm{R}_{2}\right)$ are the maxima of $\mathrm{C}_{1}$ and $\mathrm{C}_{2}$ respectively.

For Region (3): $u_{1} \geq S_{1}-R_{1}$ and $0 \leq u_{2}<S_{2}-R_{2}$,

$$
\begin{aligned}
\operatorname{Pr} & \left(C_{1} \leq u_{1}, C_{2} \leq u_{2}\right)=\operatorname{Pr}\left(C_{2} \leq u_{2}\right)=1-\operatorname{Pr}\left(C_{2}>u_{2}\right) \\
& =1-\int_{u_{2}-S_{2}+\theta}^{S_{2}-u_{2}+\theta} 2 \\
& =1-\left[\left(\mathrm{G}\left(\mathrm{~S}_{2}-u_{2}+\theta\right) d y\right.\right. \\
& \left.-\mu)-G\left(u_{2}-\mathrm{S}_{2}+\theta-\mu\right)\right]
\end{aligned}
$$

For Region (4): $0 \leq u_{1}<S_{1}-R_{1}$ and $u_{2} \geq S_{2}-R_{2}$,

$$
\begin{aligned}
& \operatorname{Pr}\left(C_{1} \leq u_{1}, C_{2} \leq u_{2}\right)=\operatorname{Pr}\left(C_{1} \leq u_{1}\right)=1-\operatorname{Pr}\left(C_{1}>u_{1}\right) \\
& \quad=1-\int_{u_{1}-S_{1}}^{S_{1}-u_{1}} g(y-\mu) d y \\
& \quad=1-\left[G\left(S_{1}-u_{1}-\mu\right)-G\left(u_{1}-S_{1}-\mu\right)\right] .
\end{aligned}
$$

For Region (5): $0 \leq u_{1}<S_{1}-R_{1}$ and $0 \leq u_{2}<S_{2}-R_{2}$, we have more than one case to consider. Before we consider the possible cases, let us first adopt the following notation:

Let $A_{1}=u_{1}-S_{1}$ (the 'rear foot" of $C_{1}$ curve)
$\mathrm{B}_{1}=\mathrm{S}_{1}-\mathrm{u}_{1}$ (the "front foot" of $\mathrm{C}_{1}$ curve)
$A_{2}=u_{2}-S_{2}+\theta_{2}$ (the 'rear foot" of $C_{2}$ curve)
$B_{2}=S_{2}-u_{2}+\theta$ (the 'front foot" of $C_{2}$ curve).

Since $S_{1}-u_{1}$ and $S_{2}-u_{2}$ are positive numbers, we have the relationship that $\mathrm{A}_{1}<\mathrm{B}_{1}$ and $\mathrm{A}_{2}<\mathrm{B}_{2}$.

With these two restrictions, there are six possible arrangements of these four values in Region (5):

Case 1: $\mathrm{A}_{1} \leq \mathrm{A}_{2}<\mathrm{B}_{1} \leq \mathrm{B}_{2}$
Case 2: $\mathrm{A}_{1}<\mathrm{B}_{1} \leq \mathrm{A}_{2}<\mathrm{B}_{2}$
Case 3: $A_{2} \leq A_{1}<B_{2} \leq B_{1}$
Case 4: $\mathrm{A}_{2}<\mathrm{B}_{2} \leq \mathrm{A}_{1}<\mathrm{B}_{1}$
Case 5: $\mathrm{A}_{1} \leq \mathrm{A}_{2}<\mathrm{B}_{2} \leq \mathrm{B}_{1}$
Case 6: $\mathrm{A}_{2} \leq \mathrm{A}_{1}<\mathrm{B}_{1} \leq \mathrm{B}_{2}$.

To prove that some of the above cases are impossible cases, we need the following lemmas:

Lemma 1: It is impossible that $A_{2} \leq A_{1}$.
Proof: Suppose $A_{2} \leq A_{1}$. By definition, we have

$$
\begin{aligned}
& u_{2}-S_{2}+\theta_{2} \leq u_{1}-S_{1}, \text { which implies } \\
& -S_{2}+\theta_{2}<\left(S_{1}-R_{1}\right)-S_{1} \text { since } 0 \leq u_{1}<S_{1}-R_{1} \text { and } \\
& 0 \leq u_{2}<S_{2}-R_{2} .
\end{aligned}
$$

This implies

$$
-\mathrm{T}_{2}-\mathrm{P}+\mathrm{T}_{1}+\mathrm{T}_{2}<-\left|\mathrm{T}_{1}-\mathrm{P}\right| \text { since }{ }_{2} \geq \mathrm{T}_{1}+\mathrm{T}_{2}
$$

Hence,

$$
\mathrm{T}_{1}-\mathrm{P}<-\left|\mathrm{T}_{1}-\mathrm{P}\right|, \text { which is impossible. }
$$

Thus, we have proved Lemma 1 by contradiction.
Lemma 2: It is impossible that $\mathrm{B}_{2} \leq \mathrm{B}_{1}$.
Proof: Suppose $B_{2} \leq B_{1}$. By definition, we have

$$
\begin{aligned}
& \mathrm{S}_{2}-\mathrm{u}_{2}+\theta_{2} \leq \mathrm{S}_{1}-\mathrm{u}_{1} \text {, which implies } \\
& \mathrm{S}_{2}-\left(\mathrm{S}_{2}-\mathrm{R}_{2}\right)+\theta_{2}<\mathrm{S}_{1}, \\
&
\end{aligned} \begin{aligned}
& 0 \leq \mathrm{u}_{1}<\mathrm{S}_{1}-R_{1} \text { and } \\
& 0 \leq u_{2}<\mathrm{S}_{2}-R_{2} .
\end{aligned}
$$

This implies

$$
\left|\mathrm{T}_{2}-\mathrm{P}\right|+\mathrm{T}_{1}+\mathrm{T}_{2}<\mathrm{T}_{1}+\mathrm{P} \text { since } \theta_{2} \geq \mathrm{T}_{1}+\mathrm{T}_{2} .
$$

Hence,

$$
\left|\mathrm{T}_{2}-\mathrm{P}\right|<\mathrm{P}-\mathrm{T}_{2}
$$

that is

$$
\left|\mathrm{P}-\mathrm{T}_{2}\right|<\mathrm{P}-\mathrm{T}_{2}, \text { which is impossible. }
$$

Again, we have proved Lemma 2 by contradiction.
Therefore, we can rule out Case 3, Case 4, and Case 6 by Lemma 1; and Case 5 by Lenma 2. There are only Cases 1 and 2 left as possible. Furthermore, we note from Figure 9 that the problem of finding $\operatorname{Pr}\left(C_{1} \leq u_{1}, C_{2} \leq u_{2}\right)$ is really a problem of finding $\operatorname{Pr}\left[y \neq\left(A_{1}, B_{1}\right) U\right.$ $\left.\left(A_{2}, B_{2}\right)\right]$, which in turn can be solved by finding $1-\operatorname{Pr}\left[y \varepsilon\left(A_{1}, B_{1}\right) \cup\left(A_{2}, B_{2}\right)\right]$.

We proceed now to find $\operatorname{Pr}\left(\mathrm{C}_{1} \leq \mathrm{u}_{1}, \mathrm{C}_{2} \leq \mathrm{u}_{2}\right)$ in Region (5): Under Case 1 , the union of $\left(A_{1}, B_{1}\right)$ and $\left(A_{2}, B_{2}\right)$ is $\left(A_{1}, B_{2}\right)$, i.e., $\left(u_{1}-S_{1}, S_{2}-u_{2}+\theta_{2}\right)$. Hence

$$
\operatorname{Pr}\left(C_{1} \leq u_{1}, C_{2} \leq u_{2}\right)=1-\left[G\left(S_{2}-u_{2}+\theta-\mu\right)-G\left(u_{1}-S_{1}-\mu\right)\right]
$$

and under Case 2, $\left(A_{1}, B_{1}\right)$ and $\left(A_{2}, B_{2}\right)$ are disjoint, the union of them is then $\left(u_{1}-S_{1}, S_{1}-u_{1}\right)$ and $\left(u_{2}-S_{2}+\theta, S_{2}-u_{2}+\theta 2\right)$. Hence

$$
\begin{aligned}
P_{2}\left(C_{1} \leq u_{1}, C_{2} \leq u_{2}\right) & -1-\left[G\left(S_{1}-u_{1}-\mu\right)-G\left(u_{1}-S_{1}-\mu\right)+G\left(S_{2}-u_{2}+\theta-\mu\right)\right. \\
& \left.-G\left(u_{2}-S_{2}+\theta 2-\mu\right)\right]
\end{aligned}
$$

To summarize, we have the following c.d.f. of $C_{1}$ and $C_{2}$, the linear coverages of Target 1 and Target 2, when a linear pattern is delivered on them:

$$
\begin{align*}
& \mathrm{F}_{\mathrm{C}_{1}}, \mathrm{C}_{2}\left(\mathrm{u}_{1}, \mathrm{u}_{2}\right)=\operatorname{Pr}\left(\mathrm{C}_{1} \leq \mathrm{u}_{1}, \mathrm{C}_{2} \leq \mathrm{u}_{2}\right) \\
& \begin{cases}0 & \text { for } u_{1}<0 \text { or } u_{2}<0 \quad \text { (Region (1)) } \\
1 & \text { for } u_{1} \geq S_{1}-R_{1} \text { and } u_{2} \geq S_{2}-R_{2} \quad \text { (Region (2)) } \\
1-G\left(S_{2}-u_{2}+\theta_{2}-\mu\right)+G\left(u_{2}-S_{2}+\theta-\mu\right) \\
& \text { for } u_{1} \geq S_{1}-R_{1} \text { and } 0 \leq u_{2}<S_{2}-R_{2} \text { (Region (3)) }\end{cases} \\
& =\left\{\begin{array}{r}
1-G\left(S_{1}-u_{1}-\mu\right)+G\left(u_{1}-S_{1}-\mu\right) \\
\text { for } 0<u_{1}< \\
1-G\left(S_{2}-u_{2}+\theta_{2}-\mu\right)+G\left(u_{1}-S_{1}-\mu\right)
\end{array}\right. \\
& \text { for } 0 \leq \mathrm{u}_{1}<\mathrm{S}_{1}-\mathrm{R}_{1} \text { and } 0 \leq \mathrm{u}_{2}<\mathrm{S}_{2}-\mathrm{R}_{2} \\
& \text { and } \mathrm{A}_{1} \leq \mathrm{A}_{2}<\mathrm{B}_{1} \leq \mathrm{B}_{2} \text { (Region (5), Case 1) } \\
& 1-G\left(S_{1}-u_{1}-\mu\right)+G\left(u_{1}-S_{1}-\mu\right)-G\left(S_{2}-u_{2}+\theta_{2}-\mu\right)+G\left(u_{2}-S_{2}+\theta-\mu\right) \\
& \text { for } 0 \leq \mathrm{u}_{1}<\mathrm{S}_{1}-\mathrm{R}_{1} \text { and } 0 \leq \mathrm{u}_{2}<\mathrm{S}_{2}-\mathrm{R}_{2} \\
& \text { and } A_{1}<B_{1} \leq A_{2}<B_{2} \text { (Region (5), Case 2) } \tag{4.5}
\end{align*}
$$

where $A_{1}, B_{1}, A_{2}$, and $B_{2}$ are defined in (4.4).
Therefore, $F\left(u_{1}, u_{2}\right)$ assumes the same form in Regions $1,2,3$ and 4; but in Region 5, it may assume different forms depending on the ordering of the values of $A_{1}, B_{1}, A_{2}$, and $B_{2}$.

Because of the different expressions in Region (5), this distribution function of two linear coverages is not easy to graph. In Figure 10 , the diagram is given for the special case exemplified by the diagram in Figure 9, where the order of arrangement is always $A_{1} \leq A_{2}<B_{1} \leq B_{2}$ (Case 1) when $\left(u_{1}, u_{2}\right)$ is in Region (5).


Figure 10. A Distribution Function of Two Linear Coverages

## 2. Some Extensions

In practice, when a linear pattern is delivered on two linear targets, a more interesting question is: 'What is the joint probabi1ity of covering Target 1 at least $u_{1}$ and covering Target 2 at least $\mathrm{u}_{2}$ ?' That is $\operatorname{Pr}\left(\mathrm{C}_{1} \geq \mathrm{u}_{1}, \mathrm{C}_{2} \geq \mathrm{u}_{2}\right)$. This question can be answered by finding $\operatorname{Pr}\left\{y \varepsilon\left[\mathrm{~A}_{1}, \mathrm{~B}_{1}\right] \cap\left[\mathrm{A}_{2}, \mathrm{~B}_{2}\right]\right\}$ in Figure 9. Expression (4.6) below answers this question for different $\left(u_{1}, u_{2}\right)$ values:

$$
\operatorname{Pr}\left(C_{1} \geq u_{1}, C_{2} \geq u_{2}\right)=\left\{\begin{array}{l}
0 \quad \text { for } u_{1}>S_{1}-R_{1} \text { or } u_{2}>S_{2}-R_{2}  \tag{4.6}\\
1 \\
\text { for } u_{1} \leq 0 \text { and } u_{2} \leq 0 \\
G\left(S_{2}-u_{2}+\theta-\mu\right)-G\left(u_{2}-S_{2}+\theta 2-\mu\right) \\
G\left(S_{1}-u_{1}-\mu\right)-G\left(u_{1}-S_{1}-\mu\right) \\
\text { for } u_{1} \leq 0 \text { and } 0<u_{2} \leq S_{2}-R_{2} \\
G\left(S_{1}-u_{1}-\mu\right)-G\left(u_{2}-S_{2}+\theta{ }_{2}-\mu\right) \\
\text { for } 0<u_{1} \leq S_{1}-R_{1} \text { and } 0<u_{2} \leq S_{1}-R_{1} \\
\quad \text { and } A_{1} \leq A_{2}<B_{1} \leq B_{2} \\
0 \quad \text { for } 0<u_{1} \leq S_{1}-R_{1} \text { and } 0<u_{2} \leq S_{1}-R_{1} \\
\text { and } A_{1}<B_{1} \leq A_{2}<B_{2} .
\end{array}\right.
$$

Furthermore, we can answer this question for any number of linear targets. Suppose, for example, we have four linear targets with a linear pattern delivered on them, then

$$
\operatorname{Pr}\left(C_{1} \geq u_{1}, C_{2} \geq u_{2}, C_{3} \geq u_{3}, C_{4} \geq u_{4}\right)=\operatorname{Pr}\left(C_{1} \geq u_{1}, C_{4} \geq u_{4}\right)
$$

provided that $u_{1}>0$ and $u_{4}>0$, and $u_{2} \leq 2 T_{2}$ and $u_{3} \leq 2 T_{3}$. These restrictions appear to be reasonable ones. The reason that we can ignore the statements about $\mathrm{C}_{2}$ and $\mathrm{C}_{3}$ in the above is that once the statements about $C_{1}$ and $C_{4}$ are satisfied, Target 2 and Target 3 must be covered completely, which means the statements about $C_{2}$ and $C_{3}$ are automatically satisfied.

In general, we have
$\operatorname{Pr}\left(C_{1} \geq u_{1}, C_{2} \geq u_{2}, \ldots, C_{n} \geq u_{n}\right)=\operatorname{Pr}\left(C_{1} \geq u_{1}, C_{n} \geq u_{n}\right)$ provided that $u_{1}>0$ and $u_{n}>0$, and $u_{i} \leq 2 T_{i}$ for $i=2,3, \ldots n-1$. Once we reduce the problem of $n$ linear coverages to a problem of two linear coverages, we can find the joint probability according to expression (4.6).

In next chapter, we shall derive the joint p.d.f. of two linear coverages from the c.d.f. of two linear coverages obtained in this chapter.

## CHAPTER V

## THE JOINT P.D.F. OF TWO LINEAR COVERAGES

We first realize that the p.d.f. of two linear coverages is neither continous nor discrete, but a mixture of them. There are four points which have positive probabilities. They are the points $(0,0)$ $\left(0, S_{2}-R_{2}\right),\left(S_{1}-R_{1}, 0\right)$, and $\left(S_{1}-R_{1}, S_{2}-R_{2}\right)$. The probabilities of these four points can be found as follows:

$$
\begin{aligned}
& \operatorname{Pr}\left(u_{1}=\right.\left.0, u_{2}=0\right) \\
&= \operatorname{Pr}\left(u_{1} \leq 0, u_{2} \leq 0\right)-\operatorname{Pr}\left(u_{1} \leq 0, u_{2}<0\right)-\operatorname{Pr}\left(u_{1}<0, u_{2} \leq 0\right) \\
& \quad+\operatorname{Pr}\left(u_{1}<0, u_{2}<0\right) \\
&= F(0,0)-F\left(0,0^{-}\right)-F\left(0^{-}, 0\right)+F\left(0^{-}, 0^{-}\right) \\
& \text {where } F\left(0,0^{-}\right)=\lim _{\ell \rightarrow 0^{-}} F(0, \ell) \\
& F\left(0^{-}, 0\right)=\lim _{\ell \rightarrow 0^{-}} F(\ell, 0) \\
& F\left(0^{-}, 0^{-}\right)=\lim _{\ell \rightarrow 0^{-}} F(\ell, k) . \\
& k \rightarrow 0^{-}
\end{aligned}
$$

According to (4.5),

$$
F(0,0)=1-G\left(S_{2}+\theta_{2}-\mu\right)+G\left(-S_{1}-\mu\right) ; \text { for }-S_{1} \leq-S_{2}+\theta_{2}<S_{1} \leq S_{2}+\theta_{2}
$$

or
$F(0,0)=1-G\left(S_{1}-\mu\right)+G\left(-S_{1}-\mu\right)-G\left(S_{2}+\theta 2-\mu\right)+G\left(-S_{2}+\theta-\mu\right)$,

$$
\text { for }-S_{1}<S_{1} \leq-S_{2}+\theta_{2}<S_{2}+\theta_{2} .
$$

Hence,
or

$$
=1-G\left(S_{1}-\mu\right)+G\left(-S_{1}-\mu\right)-G\left(S_{2}+\theta_{2}-\mu\right)+G\left(-S_{2}+\theta_{2}-\mu\right)
$$

$$
\begin{equation*}
\text { for }-S_{1}<S_{1} \leq-S_{2}+\theta_{2}<S_{2}+\theta_{2} . \tag{5.1}
\end{equation*}
$$

where, according to (4.5) ;
$\mathrm{F}\left(0, \mathrm{~S}_{2}-\mathrm{R}_{2}^{-}\right)=1-\mathrm{G}\left(\mathrm{R}_{2}+\theta_{2}-\mu\right)+\mathrm{G}\left(-\mathrm{S}_{1}-\mu\right)$ for $-\mathrm{S}_{1} \leq-\mathrm{R}_{2}+\theta_{2}<\mathrm{S}_{1} \leq \mathrm{R}_{2}+\theta_{2}$, or

$$
\begin{aligned}
& F\left(0, S_{2}^{-} R_{2}^{-}\right)=1-G\left(S_{1}-\mu\right)+G\left(-S_{1}-\mu\right)-G\left(R_{2}+\theta 2-\mu\right)+G\left(-R_{2}+\theta\right. \\
& \text { for }-S_{1}<S_{1} \leq-R_{2}+\theta_{2}<R_{2}+\theta_{2}
\end{aligned}
$$

Hence,

$$
\begin{align*}
\operatorname{Pr}\left(u_{1}\right. & \left.=0, u_{2}=S_{2}-R_{2}\right) \\
& =\left[1-G\left(S_{1}-\mu\right)+G\left(-S_{1}-\mu\right)\right]-\left[1-G\left(R_{2}+\theta_{2}-\mu\right)+G\left(-S_{1}-\mu\right)\right]-0+0 \\
& =G\left(R_{2}+\theta 2-\mu\right)-G\left(S_{1}-\mu\right) \quad \text { for }-S_{1} \leq-R_{2}+\theta 2<S_{1} \leq R_{2}+\theta_{2}, \\
& \text { or } \\
& =\left[1-G\left(S_{1}-\mu\right)+G\left(-S_{1}-\mu\right)\right]-\left[1-G\left(S_{1}-\mu\right)+G\left(-S_{1}-\mu\right)-G\left(R_{2}+\theta-\mu\right)+G\left(-R_{2}+\theta 2-\mu\right)\right] \\
& =G\left(R_{2}+\theta 2-\mu\right)-G\left(-R_{2}+\theta 2-\mu\right), \quad \text { for }-S_{1}<S_{1} \leq-R_{2}+\theta_{2}<R_{2}+\theta_{2} . \tag{5.2}
\end{align*}
$$

$$
\begin{aligned}
& \operatorname{Pr}\left(u_{1}=0, u_{2}=S_{2}-R_{2}\right) \\
& =\operatorname{Pr}\left(\mathrm{u}_{1} \leq 0, \mathrm{u}_{2} \leq \mathrm{S}_{2}-\mathrm{R}_{2}\right)-\operatorname{Pr}\left(\mathrm{u}_{1} \leq 0, \mathrm{u}_{2}<\mathrm{S}_{2}-\mathrm{R}_{2}\right)-\operatorname{Pr}\left(\mathrm{u}_{1}<0, \mathrm{u}_{2} \leq \mathrm{S}_{2}-\mathrm{R}_{2}\right) \\
& +\operatorname{Pr}\left(\mathrm{u}_{1}<0, \mathrm{u}_{2}<\mathrm{S}_{2}-\mathrm{R}_{2}\right) \\
& =F\left(0, S_{2}-R_{2}\right)-F\left(0, S_{2}-R_{2}{ }^{-}\right)-F\left(0, S_{2}-R_{2}\right)+F\left(0, S_{2}-R_{2}{ }^{-}\right)
\end{aligned}
$$

$$
\begin{aligned}
& \operatorname{Pr}\left(u_{1}=0, u_{2}=0\right) \\
& =\left[1-G\left(S_{2}+\theta 2-\mu\right)+G\left(-S_{1}-\mu\right)\right]-0-0+0=1-G\left(S_{2}+\theta 2-\mu\right)+G\left(-S_{1}-\mu\right) \\
& \text { for }-\mathrm{S}_{1} \leq-\mathrm{S}_{2}+\theta_{2}<\mathrm{S}_{1} \leq \mathrm{S}_{2}+\theta_{2} \text {, }
\end{aligned}
$$

$$
\begin{aligned}
\operatorname{Pr}\left(u_{1}=\right. & \left.S_{1}-R_{1}, u_{2}=0\right) \\
= & \operatorname{Pr}\left(u_{1} \leq S_{1}-R_{1}, u_{2} \leq 0\right)-\operatorname{Pr}\left(u_{1} \leq S_{1}-R_{1}, u_{2}<0\right) \\
& -\operatorname{Pr}\left(u_{1}<S_{1}-R_{1}, u_{2} \leq 0\right)+\operatorname{Pr}\left(u_{1}<S_{1}-R_{1}, u_{2}<0\right) \\
= & F\left(S_{1}-R_{1}, 0\right)-F\left(S_{1}-R_{1}, 0^{-}\right)-F\left(S_{1}-R_{1}^{-}, 0\right)+F\left(S_{1}-R_{1}^{-}, 0^{-}\right)
\end{aligned}
$$

where, according to (4.5),

$$
\mathrm{F}\left(\mathrm{~S}_{1}-\mathrm{R}_{1}^{-}, 0\right)=1-\mathrm{G}\left(\mathrm{~S}_{2}+\theta_{2}-\mu\right)+\mathrm{G}\left(-\mathrm{R}_{1}-\mu\right) \quad \text { for }-\mathrm{R}_{1} \leq-\mathrm{S}_{2}+\theta_{2}<\mathrm{R}_{1} \leq \mathrm{S}_{2}+\theta_{2}
$$

or

$$
\begin{aligned}
& \mathrm{F}\left(\mathrm{~S}_{1}-\mathrm{R}_{1}^{-}, 0\right)=1-\mathrm{G}\left(\mathrm{R}_{1}-\mu\right)+\mathrm{G}\left(-\mathrm{R}_{1}-\mu\right)-\mathrm{G}\left(\mathrm{~S}_{2}+\theta_{2}-\mu\right)+\mathrm{G}\left(-\mathrm{S}_{2}+\theta_{2}-\mu\right) \\
& \text { for }-\mathrm{R}_{1}<\mathrm{R}_{1} \leq-\mathrm{S}_{2}+\theta 2<\mathrm{S}_{2}+\theta
\end{aligned}
$$

Hence,

$$
\begin{align*}
& \operatorname{Pr}\left(u_{1}\right. \\
&\left.=S_{1}-R_{1}, u_{2}=0\right) \\
&=\left[1-G\left(S_{2}+\theta-\mu\right)+G\left(-S_{2}+\theta 2-\mu\right)\right]-0-\left[1-G\left(S_{2}+\theta_{2}-\mu\right)+G\left(-R_{1}-\mu\right)\right]+0 \\
&=G\left(-S_{2}+\theta_{2}-\mu\right)-G\left(-R_{1}-\mu\right) \text { for }-R_{1} \leq-S_{2}+\theta_{2}<R_{1} \leq S_{2}+\theta_{2}, \\
& \text { or } \\
&=\left[1-G\left(S_{2}+\theta_{2}-\mu\right)+G\left(-S_{2}+\theta 2-\mu\right)\right]-\left[1-G\left(R_{1}-\mu\right)+G\left(-R_{1}-\mu\right)-G\left(S_{2}+\theta_{2}-\mu\right)+G\left(-S_{2}+\theta_{2}-\mu\right)\right]  \tag{5.3}\\
&=G\left(R_{1}-\mu\right)+G\left(-R_{1}-\mu\right) \text { for }-R_{1}<R_{1} \leq-S_{2}+\theta_{2}<S_{2}+\theta_{2} .
\end{align*}
$$

Finally,

$$
\begin{aligned}
\operatorname{Pr}\left(u_{1}=\right. & \left.S_{1}-R_{1}, u_{2}=S_{2}-R_{2}\right) \\
= & \operatorname{Pr}\left(u_{1} \leq S_{1}-R_{1}, u_{2} \leq S_{2}-R_{2}\right)-\operatorname{Pr}\left(u_{1} \leq S_{1}-R_{1}, u_{2}<S_{2}-R_{2}\right) \\
& -\operatorname{Pr}\left(u_{1}<S_{1}-R_{1}, u_{2} \leq S_{2}-R_{2}\right)+\operatorname{Pr}\left(u_{1}<S_{1}-R_{1}, u_{2}<S_{2}-R_{2}\right) \\
= & F\left(S_{1}-R_{1}, S_{2}-R_{2}\right)-F\left(S_{1}-R_{1}, S_{2}-R_{2}-\right)-F\left(S_{1}-R_{1}-, S_{2}-R_{2}\right)+F\left(S_{1}-R_{1}-, S_{2}-R_{2}\right)
\end{aligned}
$$

where, according to (4.5),

$$
\begin{aligned}
& \mathrm{F}\left(\mathrm{~S}_{1}-\mathrm{R}_{1}^{-}, \mathrm{S}_{2}-\mathrm{R}_{2}^{-}\right)=1-\mathrm{G}\left(\mathrm{R}_{2}+\theta 2-\mu\right)+\mathrm{G}\left(-\mathrm{R}_{1}-\mu\right) \\
& \\
& \text { for }-\mathrm{R}_{1} \leq-\mathrm{R}_{2}+\theta_{2}<\mathrm{R}_{1} \leq \mathrm{R}_{2}+\theta_{2},
\end{aligned}
$$

or

$$
\begin{array}{r}
\mathrm{F}\left(\mathrm{~S}_{1}-\mathrm{R}_{1}^{-}, \mathrm{S}_{2}-\mathrm{R}_{2}^{-}\right)=1-\mathrm{G}\left(\mathrm{R}_{1}-\mu\right)+\mathrm{G}\left(-\mathrm{R}_{1}-\mu\right)-\mathrm{G}\left(\mathrm{R}_{2}+\theta 2-\mu\right)+\mathrm{G}\left(-\mathrm{R}_{2}+\theta 2-\mu\right) \\
\text { for }-\mathrm{R}_{1}<\mathrm{R}_{1} \leq-\mathrm{R}_{2}+\theta 2<\mathrm{R}_{2}+\theta 2 .
\end{array}
$$

Ilence,

$$
\begin{align*}
\operatorname{Pr}\left(u_{1}=\right. & \left.S_{1}-R_{1}, u_{2}=S_{2}-R_{2}\right) \\
= & 1-\left[1-G\left(R_{2}+\theta 2-\mu\right)+G\left(-R_{2}+\theta 2-\mu\right)\right]-\left[1-G\left(R_{1}-\mu\right)+G\left(-R_{1}-\mu\right)\right] \\
& +\left[1-G\left(R_{2}+\theta 2-\mu\right)+G\left(-R_{1}-\mu\right)\right] \\
= & G\left(R_{1}-\mu\right)-G\left(-R_{2}+\theta 2-\mu\right) \text { for }-R_{1} \leq-R_{2}+\theta 2<R_{1} \leq R_{2}+\theta 2, \\
& \text { or } \\
= & 1-\left[1-G\left(R_{2}+\theta 2-\mu\right)+G\left(-R_{2}+\theta 2-\mu\right)\right]-\left[1-G\left(R_{1}-\mu\right)+G\left(-R_{1}-\mu\right)\right] \\
& +\left[1-G\left(R_{1}-\mu\right)+G\left(-R_{1}-\mu\right)-G\left(R_{2}+\theta 2-\mu\right)+G\left(-R_{2}+\theta 2-\mu\right)\right] \\
= & 0 \quad \text { for }-R_{1}<R_{1} \leq-R_{2}+\theta<R_{2}+\theta_{2} . \tag{5.4}
\end{align*}
$$

Besides these four points, whose probabilities were obtained in (5.1), (5.2), (5.3), and (5.4) above, the remaining probability is concentrated on four open intervals:

$$
\begin{aligned}
& \left\{\left(u_{1}, u_{2}\right) \mid u_{1}=0,0<u_{2}<S_{2}-R_{2}\right\} \\
& \left\{\left(u_{1}, u_{2}\right) \mid 0<u_{1}<S_{1}-R_{1}, u_{2}=0\right\} \\
& \left\{\left(u_{1}, u_{2}\right) \mid u_{1}=S_{1}-R_{1}, 0<u_{2}<S_{2}-R_{2}\right\} \\
& \left\{\left(u_{1}, u_{2}\right) \mid 0<u_{1}<S_{1}-R_{1}, u_{2}=S_{2}-R_{2}\right\} .
\end{aligned}
$$

The probability mass concentration on these four open intervals can be obtained by following a similar argument by which we obtained expressions (5.1), (5.2), (5.3), and (5.4). We decline to do it because of the following reasons: Firstly, for each open interval, we shall have three alternative expression depending on the order of arrangement of $A_{1}, A_{2}$,
$\mathrm{B}_{1}$, and $\mathrm{B}_{2}$. Secondly, these probabilities are not essential in deriving the joint p.d.f. of two linear coverages.

Apart from these four points and four open interval, the remaining portion of the $U_{1} U_{2}$ plane contributes no probability to the joint distribution function $F\left(u_{1}, u_{2}\right)$. In other words, the joint p.d.f. for the remaining portion is 0 . This can be shown by taking derivatives twice on $F\left(u_{1}, u_{2}\right)$ with respect to $u_{1}$ first and then with respect to $u_{2}$.

Since this distribution function is a mixture of continuous and discret distributions, the values of the function $F\left(u_{1}, u_{2}\right)$ come from the p.d.f., $f\left(u_{1}, u_{2}\right)$, by summing over (1) the probabilities of the points which have positive values and belong to the region $\left\{(x, y) \mid x \leq u_{1}, y \leq u_{2}\right\}$; and (2) the areas of the "walls" whose "base lines" belong to the region $\left\{(x, y) \mid x \leq u_{1}, y \leq u_{2}\right\}$. There are four walls built around the rectangle $\left\{(x, y) \mid 0 \leq x \leq S_{1}-R_{1}, 0 \leq y \leq S_{2}-R_{2}\right\}$. The value of $F\left(u_{1}, u_{2}\right)$ on these four base lines (open intervals) are obtained from (4.5) to be:
$F\left(u_{1}, u_{2}\right)$

We can now proceed to derive the p.d.f. of $\left(C_{1}, C_{2}\right), f\left(u_{1}, u_{2}\right)$. As we have indicated before, all the probability mass is concentrated on the four points and four open intervals. The values of $f\left(u_{1}, u_{2}\right)$ on the four points have been obtained in (5.1), (5.2), (5.3), and (5.4). What follows will give us the values of $f\left(u_{1}, u_{2}\right)$ on the four open intervals.

The value of $f\left(u_{1}, u_{2}\right)$ in the open interval $u_{1}=0,0<u_{2}<S_{2}-R_{2}$ can be obtained by directly taking the derivative of $F\left(u_{1}, u_{2}\right)$ from (5.5) with respect to $u_{2}$. Namely:

$$
\begin{aligned}
& f\left(u_{1}, u_{2}\right)=\frac{\alpha}{\alpha u_{2}}\left[1-G\left(S_{2}-u_{2}+\theta_{2}-\mu\right)+G\left(-S_{1}-\mu\right)\right]=g\left(S_{2}-u_{2}+\theta-\mu\right) \\
& \text { for } u_{1}=0,0<u_{2}<S_{2}-R_{2} \text { and }-S_{1} \leq u_{2}-S_{2}+\theta 2<S_{1} \leq S_{2}-u_{2}+\theta_{2}
\end{aligned}
$$

or

$$
\begin{align*}
f\left(u_{1}, u_{2}\right) & =\frac{\alpha}{\alpha u_{2}}\left[1-G\left(S_{1}-\mu\right)+G\left(-S_{1}-\mu\right)-G\left(S_{2}-u_{2}+\theta-\mu\right)+G\left(u_{2}-S_{2}+\theta 2-\mu\right)\right] \\
& =g\left(S_{2}-u_{2}+\theta-\mu\right)+g\left(u_{2}-S_{2}+\theta-\mu\right) \\
& \text { for } u_{1}=0,0<u_{2}<S_{2}-R_{2} \text { and }-S_{1}<S_{1} \leq u_{2}-S_{2}+\theta<S_{2}-u_{2}+\theta_{2} . \tag{5.6}
\end{align*}
$$

The value of $f\left(u_{1}, u_{2}\right)$ in the open interval $0<u_{1}<S_{1}-R_{1}, u_{2}=0$ is similarly obtained by taking the derivative of $F\left(u_{1}, u_{2}\right)$ with respect to $u_{1}$ :

$$
\begin{aligned}
& f\left(u_{1}, u_{2}\right)=\frac{\alpha}{\alpha u_{1}}\left[1-G\left(S_{2}+\theta_{2}-\mu\right)+G\left(u_{1}-S_{1}-\mu\right)\right]=g\left(u_{1}-S_{1}-\mu\right) \\
& \quad \text { for } 0<u_{1}<S_{1}-R_{1}, u_{2}=0 \text { and } u_{1}-S_{1} \leq-S_{2}+\theta<S_{1}-\mu_{1} \leq S_{2}+\theta_{2},
\end{aligned}
$$

or

$$
\begin{align*}
f\left(u_{1}, u_{2}\right) & =\frac{\alpha}{\alpha u_{1}}\left[1-G\left(S_{1}-u_{1}-\mu\right)+G\left(u_{1}-S_{1}-\mu\right)-G\left(S_{2}+\theta-\mu\right)+G\left(-S_{2}+\theta 2-\mu\right)\right] \\
& =g\left(S_{1}-u_{1}-\mu\right)+g\left(u_{1}-S_{1}-\mu\right) \\
& \text { for } 0<u_{1}<S_{1}-R_{1}, u_{2}=0 \text { and } u_{1}-S_{1}<S_{1}-u_{1} \leq-S_{2}+\theta_{2}<S_{2}+\theta_{2} . \tag{5.7}
\end{align*}
$$

As for the open interval $u_{1}=S_{1}-R_{1}, 0<u_{2}<S_{2}-R_{2}$, we must be more careful. Taking the derivative of $F\left(u_{1}, u_{2}\right)$ with respect to $u_{2}$ will not give us the correct $f\left(u_{1}, u_{2}\right)$ in this open interval. Before we present the correct way to find $f\left(u_{1}, u_{2}\right)$ in this interval, let us take a closer look at the nature of $F\left(u_{1}, u_{2}\right)$ in this interval.
Figure 11 shows how the value of $F\left(u_{1}, u_{2}\right)$ increases when $u_{2}$ moves along this interval from $\left(u_{1}=S_{1}-R_{1}, u_{2}=0^{+}\right)$to $\left(u_{1}=S_{1}-R_{1}, u_{2}=\left(S_{2}-R_{2}\right)^{-}\right)$:


Figure 11. When $u_{2}$ Increases Along the Interval

$$
u_{1}=S_{1}-R_{1}, \quad 0<u_{2}<S_{2}-R_{2}
$$

As $u_{2}$ increases along this interval, the value of $F\left(u_{1}, u_{2}\right)$ will increase too. The point we are trying to make here is that the increasing of the $F\left(u_{1}, u_{2}\right)$ value does not merely come from the probability mass of the interval $u_{1}=S_{1}-R_{1}, 0<u_{2}<S_{2}-R_{2}$, but it also comes from the probability mass of the interval $u_{1}=0,0<u_{2}<S_{2}-R_{2}$. Therefore, before we take the derivative of $F\left(u_{1}, u_{2}\right)$, we have to subtract this extra contribution of probability mass coming from the interval $u_{1}=0,0<u_{2}<S_{2}-R_{2}$. Let us do this.
[ $F\left(u_{1}, u_{2}\right)$ in the interval $\left.u_{1}=S_{1}-R_{1}, 0<u_{2}<S_{2}-R_{2}\right]-$
$\left[\mathrm{F}\left(\mathrm{u}_{1}, \mathrm{u}_{2}\right)\right.$ in the interval $\left.\mathrm{u}_{1}=0,0<\mathrm{u}_{2}<\mathrm{S}_{2}-\mathrm{R}_{2}\right]$
$=\left[1-G\left(S_{2}-u_{2}+\theta_{2}-\mu\right)+G\left(u_{2}-S_{2}+\theta_{2}-\mu\right)\right]-\left[1-G\left(S_{2}-u_{2}+\theta-\mu\right)+G\left(-S_{1}-\mu\right)\right]$
$=G\left(u_{2}-S_{2}+\theta_{2}-\mu\right)-G\left(-S_{1}-\mu\right)$
for $-S_{1} \leq u_{2}-S_{2}+\theta_{2}<S_{1} \leq S_{2}-u_{2}+\theta$,
or $=\left[1-G\left(\mathrm{~S}_{2}-\mathrm{u}_{2}+\theta 2-\mu\right)+\mathrm{G}\left(\mathrm{u}_{2}-\mathrm{S}_{2}+\theta_{2}-\mu\right)\right]$
$-\left[1-G\left(S_{1}-\mu\right)+G\left(-S_{1}-\mu\right)-G\left(S_{2}-u_{2}+\theta-\mu\right)+G\left(u_{2}-S_{2}+\theta 2-\mu\right)\right]$
$=G\left(S_{1}-\mu\right)+G\left(-S_{1}-\mu\right)$
for $-\mathrm{S}_{1}<\mathrm{S}_{1} \leq \mathrm{u}_{2}-\mathrm{S}_{2}+{ }_{2}<\mathrm{S}_{2}-\mathrm{u}_{2}+\theta_{2}$.

Now we can take the derivative of (5.8) with respect to $u_{2}$ and get $f\left(u_{1}, u_{2}\right)$ in this open interval:
$f\left(u_{1}, u_{2}\right)=\left\{\begin{array}{r}g\left(u_{2}-S_{2}+\theta 2-\mu\right) \\ \quad \text { for } \quad u_{1}=S_{1}-R_{1}, 0<u_{2}<S_{2}-R_{2}, \text { and } \\ -S_{1} \leq u_{2}-S_{2}+\theta 2<S_{1} \leq S_{2}-u_{2}+\theta 2 \\ 0 \quad\end{array} \quad \begin{array}{r}\text { for } u_{1}=S_{1}-R_{1}, 0<u_{2}<S_{2}-R_{2}, \text { and } \\ -S_{1}<S_{1} \leq u_{2}-S_{2}+\theta_{2}<S_{2}-u_{2}+\theta_{2} .\end{array}\right.$
The same precaution must be taken when we derive $f\left(u_{1}, u_{2}\right)$ for the open interval $0<u_{1}<S_{1}-R_{1}, u_{2}=S_{2}-R_{2}$. Following a similar argument, we take the derivative of
[ $\mathrm{F}\left(\mathrm{u}_{1}, \mathrm{u}_{2}\right)$ in the interval $0<\mathrm{u}_{1}<\mathrm{S}_{1}-\mathrm{R}_{1}, \mathrm{u}_{2}=\mathrm{S}_{2}-\mathrm{R}_{2}$ ]-
[ $F\left(u_{1}, u_{2}\right)$ in the interval $\left.0<u_{1}<S_{1}-R_{1}, u_{2}=0\right]$
and get:

$$
f\left(u_{1}, u_{2}\right)=\left\{\begin{array}{r}
\begin{array}{r}
\left(S_{1}-u_{1}-\mu\right) \\
\\
\text { for } \quad 0<u_{1}<S_{1}-R_{1}, u_{2}=S_{2}-R_{2},
\end{array} \quad \text { and }  \tag{5.10}\\
\quad u_{1}-S_{1} \leq-S_{2}+\theta 2<S_{1}-u_{1} \leq S_{2}+\theta \\
0 \quad \text { for } 0<u_{1}<S_{1}-R_{1}, u_{2}=S_{2}-R_{2}, \text { and } \\
\quad u_{1}-S_{1}<S_{1}-u_{1} \leq-S_{2}+\theta_{2}<S_{2}+\theta
\end{array}\right.
$$

To summarize, we put (5.1), (5.2), (5.3), (5.4), (5.6), (5.7), (5.9) and (5.10) together. Expression (5.11) below gives the joint probability density function of two linear coverages, which is a mixed p.d.f:

$$
\begin{aligned}
& \mathrm{f}_{\mathrm{C}_{1}}, \mathrm{C}_{2}\left(\mathrm{u}_{1}, \mathrm{u}_{2}\right)= \\
& 1-G\left(S_{2}+\theta_{2}-\mu\right)+G\left(-S_{1}-\mu\right) \\
& \text { for } u_{1}=0, u_{2}=0 \text {, and }-S_{1} \leq-S_{2}+\theta_{2}<S_{1} \leq S_{2}+\theta_{2} \\
& 1-G\left(S_{1}-\mu\right)+G\left(-S_{1}-\mu\right)-G\left(S_{2}+\theta-\mu\right)+G\left(-S_{2}+\theta_{2}+\mu\right) \\
& \text { for } u_{1}=0, u_{2}=0 \text {, and }-S_{1}<S_{1} \leq-S_{2}+\theta_{2}<S_{2}+\theta 2 \\
& G\left(R_{2}+\theta 2-\mu\right)-G\left(S_{1}-\mu\right) \\
& \text { for } u_{1}=0, u_{2}=S_{2}-R_{2} \text {, and }-S_{1} \leq-R_{2}+\theta_{2}<S_{1} \leq R_{2}+\theta_{2} \\
& G\left(R_{2}+\theta 2^{-\mu)}-G\left(-R_{2}+\theta 2^{-\mu)}\right.\right. \\
& \text { for } u_{1}=0, u_{2}=S_{2}-R_{2} \text {, and }-S_{1}<S_{1} \leq-R_{2}+\theta_{2}<R_{2}-\theta_{2} \\
& \mathrm{G}\left(-\mathrm{S}_{2}+\theta_{2}-\mu\right)-\mathrm{G}\left(-\mathrm{R}_{1}-\mu\right) \\
& \text { for } u_{1}=S_{1}-R_{1}, u_{2}=0 \text {, and }-R_{1} \leq-S_{2}+\theta_{2}<R_{1} \leq S_{2}+\theta_{2} \\
& G\left(R_{1}-\mu\right)+G\left(-R_{1}-\mu\right) \\
& \text { for } u_{1}=S_{1}-R_{1}, u_{2}=0 \text {, and }-R_{1}<R_{1} \leq-S_{2}+\theta_{2}<S_{2}+\theta_{2} \text {. }
\end{aligned}
$$

$$
\begin{aligned}
& G\left(R_{1}-\mu\right)-G\left(-R_{2}+\theta{ }_{2}-\mu\right) \\
& \text { for } u_{1}=S_{1}-R_{1}, u_{2}=S_{2}-R_{2} \text {, and }-R_{1} \leq-R_{2}+\theta_{2}<R_{1} \leq R_{2}+\theta_{2} \\
& 0
\end{aligned}
$$

$$
\begin{align*}
& g\left(u_{1}-S_{1}-\mu\right) \\
& \text { for } 0<u_{1}<S_{1}-R_{1}, u_{2}=0 \text {, and } u_{1}-S_{1} \leq-S_{2}+\theta_{2}<S_{1}-u_{1} \leq S_{2}+\theta_{2} \\
& g\left(u_{1}-S_{1}-\mu\right)+g\left(S_{1}-u_{1}-\mu\right) \\
& \text { for } 0<u_{1}<S_{1}-R_{1}, u_{2}=0 \text {, and } u_{1}-S_{1}<S_{1}-u_{1} \leq-S_{2}+\theta 2<S_{2}+\theta 2 \\
& g\left(u_{2}-S_{2}+\theta 2^{-\mu}\right) \\
& \text { for } u_{1}=S_{1}-R_{1}, 0<u_{2}<S_{2}-R_{2} \text {, and }-S_{1} \leq u_{2}-S_{2}+\theta_{2}<S_{1} \leq S_{2}-u_{2}+\theta_{2} \\
& 0 \\
& \text { for } u_{1}=S_{1}-R_{1}, 0<u_{2}<S_{2}-R_{2} \text {, and }-S_{1}<S_{1} \leq u_{2}-S_{2}+\theta_{2}<S_{2}-u_{2}+\theta_{2} \\
& g\left(S_{1}-u_{1}-\mu\right) \\
& \text { for } 0<u_{1}<S_{1}-R_{1}, u_{2}=S_{2}-R_{2} \text {, and } u_{1}-S_{1} \leq-S_{2}+\theta 2<S_{1}-u_{1} \leq S_{2}^{+\theta} 2 \\
& 0 \\
& \text { for } 0<u_{1}<S_{1}-R_{1}, u_{2}=S_{2}-R_{2} \text {, and } u_{1}-S_{1}<S_{1}-u_{1} \leq-S_{2}+\theta 2<S_{2}+\theta_{2} \\
& 0 \text { otherwise. } \tag{5.11}
\end{align*}
$$

In Figure 12, we give a diagram to show how this p.d.f. may look like. Again this diagram is a special case where the order of arrangement is always $A_{1} \leq A_{2}<B_{1} \leq B_{2}$ when $\left(u_{1}, u_{2}\right)$ is in region (5).


Figure 12. A p.d.f. of Two Linear Coverages

After we have obtained the joint c.d.f. and the joint p.d.f. of two linear coverages, the natural extension is to consider the joint c.d.f. of two rectangular coverages. The mathematical expression for it will be obtained in next chapter, however, unfortunately, this expression is of little practical usage as will be seen shortly.

CHAPTER VI

THE JOINT C.D.F. OF TWO RECTANGULAR COVFRAGFS

## 1. An Attempt to Use the Joint p.d.f. <br> of Two Linear Coverages

In this chapter, we shall consider the situation where a rectangular pattern is delivered on two rectangular targets. To find this joint c.d.f. of two rectangular coverages, our first temptation is to make use of the joint p.d.f. of two linear targets which we have derived in Chapter V.

If we consider $f_{C_{1}}, C_{2}\left(u_{1}, u_{2}\right)$ in expression (5.11) as the joint p.d.f. of two linear coverages in the range direction, we may then use a similar argument to obtain the joint p.d.f. of two linear coverages in the deflection direction, $f_{C_{1}}{ }^{\prime}, C_{2}{ }^{\prime}\left(u_{1}{ }^{\prime}, u_{2}{ }^{\prime}\right)$. Due to the fact that the two random vectors $\left(C_{1}, C_{2}\right)$ and $\left(C_{1}{ }^{\prime}, C_{2}{ }^{\prime}\right)$ are independent, we shall have the joint p.d.f. of $\left(C_{1}, C_{2}, C_{1}{ }^{\prime}, C_{2}{ }^{\prime}\right)$ as the product of them, i.e.,

$$
\begin{equation*}
\mathrm{f}_{\mathrm{C}_{1}}, \mathrm{C}_{2}, \mathrm{C}_{1}^{\prime}, \mathrm{C}_{2},\left(\mathrm{u}_{1}, u_{2}, u_{1}^{\prime}, u_{2}^{\prime}\right)=\mathrm{f}_{\mathrm{C}_{1}}, \mathrm{C}_{2}\left(\mathrm{u}_{1}, u_{2}\right) \cdot \mathrm{f}_{\mathrm{C}_{1}}, \mathrm{C}_{2}\left(\mathrm{u}_{1}^{\prime}, u_{2}\right) \tag{6.1}
\end{equation*}
$$

Now letting $z_{1}, z_{2}$ be the rectangular coverages of Target 1 and Target 2 respectively, we shall have the following relationships:

$$
\begin{aligned}
z_{1} & =C_{1} \cdot C_{1}^{\prime} \\
\text { and } z_{2} & =C_{2} \cdot C_{2}^{\prime}
\end{aligned}
$$

Theoretically, the joint p.d.f. of $z_{1}$ and $z_{2}$ can be obtained by integrating (summing) the joint p.d.f. in expression (6.1) over the proper regions that is

$$
\begin{align*}
& F_{z_{1},} z_{2}\left(v_{1}, v_{2}\right)=\operatorname{Pr}\left(z_{1} \leq v_{1}, z_{2} \leq v_{2}\right) \\
&=\int_{\left(u_{2}, u_{2}^{\prime}\right)} \int_{\varepsilon_{3}} \int_{\left(u_{1}, u_{1}^{\prime}\right) \int_{\mathcal{A}}} d F\left(u_{1}, u_{2}, u_{1}^{\prime}, u_{2}^{\prime}\right) \tag{6.2}
\end{align*}
$$

where $\mathcal{A}=\left\{\left(\mathrm{u}_{1}, \mathrm{u}_{1}^{\prime}\right) \mid 0 \leq \mathrm{u}_{1} \leq \mathrm{S}_{1}-\mathrm{R}_{1}, \quad 0 \leq \mathrm{u}_{1}^{\prime} \leq \mathrm{S}_{1}^{\prime}-\mathrm{R}_{1}^{\prime}\right\}$

$$
-\left\{\left(u_{1}, u_{1}^{\prime}\right) \left\lvert\, \frac{v_{1}}{u_{1}^{\prime}}<u_{1} \leq S_{1}-R_{1}\right., \quad \frac{v_{1}}{S_{1}-R_{1}}<u_{1}^{\prime} \leq S_{1}^{\prime}-R_{1}^{\prime}\right\}
$$


and $\beta=\left\{\left(u_{2}, u_{2}^{\prime}\right) \mid 0 \leq u_{2} \leq S_{2}-R_{2}, \quad 0 \leq u_{2}^{\prime} \leq S_{2}^{\prime}-R_{2}^{\prime}\right\}$

$$
-\left\{\left(u_{2}, u_{2}^{\prime}\right) \left\lvert\, \frac{v_{2}}{u_{2}^{\prime}}<u_{2} \leq S_{2}-R_{2}\right., \frac{v_{2}}{S_{2}-R_{2}}<u_{2}^{\prime} \leq S_{2}^{\prime}-R_{2}^{\prime}\right\}
$$



Although the joint p.d.f. of $\left(C_{1}, C_{2}, C_{1}{ }^{\prime}, C_{2}{ }^{\prime}\right)$ can be obtained explicitly for (6.2), to carry out the integration in (6.2) is by no means an easy task. First of all, the joint p.d.f. of $\left(C_{1}, C_{2}, C_{1}{ }^{\prime}, C_{2}{ }^{\prime}\right)$ in (6.1) is a multiple-faceted function defined in four-dimensional space. To make things worse, this is a joint p.d.f. of a mixed random vector. This means that when we integrate over the proper region, we have to sum up the probability mass of some points, some areas, and some volumes in this four-dimensional space. If this is not impossible, it is certainly not feasible.

In the next section, we shall consider another approach.

## 2. An Alternative Approach

Another way to look at this problem of finding the joint c.d.f. of two rectangular coverages is to find the right region on the two-dimensional plane such that the event $\left(Z_{1} \leq v_{1}\right.$ and $\left.Z_{2} \leq v_{2}\right)$ will be satisfied when the center of the pattern falls within that region. This approach was used by Gay and Weeks (1973) in their derivation of the c.d.f. of one rectangular coverage. In the case of one rectangular target, the region corresponding to the event ( $Z \leq v$ ) for $0 \leq v<(S-R)\left(S^{\prime}-R^{\prime}\right)$ is the complement of $D$ in Figure 13 on next page.

$$
\begin{aligned}
& \left\{\begin{array}{l}
\theta^{\prime}-R^{\prime} \leq y^{\prime} \leq \theta^{\prime}+R^{\prime} \\
y=\theta+S^{v} \%\left(S^{\prime}-R^{\prime}\right)
\end{array}\right\}
\end{aligned}
$$

all the curves at the four corners are defined as $|y-\theta| \cdot\left|y^{\prime}-\theta^{\prime}\right|-S^{\prime}|y-\theta|-S\left|y^{\prime}-\theta^{\prime}\right|+S \cdot S^{\prime}=v$.

Figure 13. The Region Corresponding to the Event ( $Z \leq v$ )

The boundary of the region D consists of two segments in the range direction $(|\mid)$, two segments in the deflection direction (二), and the curves at the corners $\left(\begin{array}{l}r \\ 1 \\ j\end{array}\right)$ ). An expression defining the four curves may be obtained if we realize that (2.2) can be simplified to
$C=h(y)= \begin{cases}0 & \text { when } y \leq-S+\theta \text { or } y \geq S+\theta \\ S-R & \text { when }-R+\theta \leq y \leq R+\theta \\ S-|y-\theta| & \text { when }-S+\theta<y<-R+\theta \text { or } R+\theta<y<S+\theta\end{cases}$
and that

$$
v=C \cdot C^{\prime}=(S-|y-\theta|)\left(S^{\prime}-\left|y^{\prime}-\theta^{\prime}\right|\right)=|y-\theta| \cdot\left|y^{\prime}-\theta^{\prime}\right|-S^{\prime}|y-\theta|-S\left|y^{\prime}-\theta^{\prime}\right|+S \cdot S^{\prime} .
$$

The definition of the boundary used in Figure 13 is equivalent to that used by Gay and Weeks (1973, p. 10, Table 5).

Thus the way they obtained the c.d.f. of a rectangular coverage for $0 \leq v<(S-R)\left(S^{\prime}-R^{\prime}\right)$ was essentially

$$
\begin{aligned}
F_{Z}(v) & =\operatorname{Pr}[z \leq v]=\operatorname{Pr}\left[\left(Y, Y^{\prime}\right) \notin D\right] \\
& =1-\iint_{D} f\left(y, y^{\prime}\right) d y d y^{\prime}
\end{aligned}
$$

where $D$ is defined in Figure 13 and $f\left(y, y^{\prime}\right)$ is defined in (2.1). For $v<0$ and $v \geq(S-R)\left(S^{\prime}-R^{\prime}\right)$, the values of $F_{z}(v)$ are 0 and 1 respectively.

If instead of one target, we have two targets under consideration, we certainly can construct two regions around Target 1 and Target 2 in exactly the same way that we constructed the D region illustrated in Figure 13. The diagram for two targets may look like what is shown in Figure 14.


Figure 14. The Region Corresponding to the Event

$$
\left(z_{1} \leq v_{1}, z_{2} \leq v_{2}\right)
$$

The bounderies of $D_{1}$ and $D_{2}$ can be obtained by subscripting the $R, S$, $\theta$, and v in Figure 13 with ' 1 " and " 2 ".

It is clear from this diagram that the joint p.d.f. of two rectangular coverages for $0 \leq \mathrm{v}_{1}<\left(\mathrm{S}_{1}-\mathrm{R}_{1}\right)\left(\mathrm{S}_{1}^{\prime}-\mathrm{R}_{1}{ }^{\prime}\right)$ and $0 \leq v_{2}<\left(S_{2}-R_{2}\right)\left(S_{2}^{\prime}-R_{2}^{\prime}\right)$, can be obtained by integrating over all the plane outside $D_{1} \cup D_{2}$, that is,

$$
\begin{align*}
& \mathrm{F}_{Z_{1},}, Z_{2}\left(v_{1}, v_{2}\right)=\operatorname{Pr}\left[Z_{1} \leq v_{1}, Z_{2} \leq v_{2}\right]=\operatorname{Pr}\left[\left(Y, Y^{\prime}\right) \notin D_{1} \cup D_{2}\right] \\
& =1-\operatorname{Pr}\left[\left(Y, Y^{\prime}\right) \varepsilon D_{1} \cup D_{2}\right] \\
& =1-\left[\iint_{D_{1}} f\left(y, y^{\prime}\right) d y d y^{\prime}+\int_{D_{2}} \int f\left(y, y^{\prime}\right) d y d y^{\prime}-\int_{D_{1} \cap D_{2}} f\left(y, y^{\prime}\right)\right. \\
& \text { for } 0 \leq v_{1}<\left(S_{1}-R_{1}\right)\left(S_{1}^{\prime}-R_{1}^{\prime}\right) \text { and } \\
& 0 \leq v_{2}<\left(S_{2}-R_{2}\right)\left(S_{2}^{\prime}-R_{2}^{\prime}\right) \tag{6.3}
\end{align*}
$$

For $\left(v_{1}, v_{2}\right)$ values other then that defined above, we have:

$$
\begin{align*}
& \mathrm{F}_{z_{1}, Z_{2}\left(v_{1}, v_{2}\right)} \begin{array}{ll}
0 & \text { for } v_{1}<0 \text { or } v_{2}<0 \\
1 & \text { for } v_{1} \geq\left(S_{1}-R_{1}\right)\left(S_{1}^{\prime}-R_{1}^{\prime}\right) \\
1-\iint_{D_{1}} \int f\left(y, y^{\prime}\right) d y d y^{\prime} & \text { and } v_{2} \geq\left(S_{2}-R_{2}\right)\left(S_{2}^{\prime}-R_{2}^{\prime}\right) \\
1-\iint_{D_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime} & \text { for } v_{1} \geq\left(S_{1}-R_{1}\right)\left(S_{1}^{\prime}-R_{1}\right)\left(S_{1}^{\prime}-R_{1}^{\prime}\right)
\end{array} \\
& =\begin{array}{ll}
\text { and } v_{2} \geq\left(S_{2}-R_{2}\right)\left(S_{2}^{\prime}-R_{2}^{\prime}\right)
\end{array}
\end{align*}
$$

We note that in (6.3) and (6.3a)

$$
\iint_{D_{1}} f\left(y, y^{\prime}\right) d y d y^{\prime}=\operatorname{Pr}\left(z_{1}>v_{1}\right)=1-\operatorname{Pr}\left(z_{1} \leq v_{1}\right)=1-F_{z_{1}}\left(v_{1}\right)
$$

which is, by expression (3.3),

$$
\begin{aligned}
& 1-\left[G \left({ }^{V 1} /\left(S_{1}^{\prime}-R_{1}^{\prime}\right)^{\left.-S_{1}-\mu\right)+G\left({ }^{V 1} /\left(S_{1}^{\prime}-R_{1}^{\prime}\right)^{\left.-S_{1}+\mu\right)}\right] \cdot\left[1-G\left(-R_{1}^{\prime}-\mu^{\prime}\right)-G\left(-R_{1}^{\prime}+\mu^{\prime}\right)\right]}\right.\right.
\end{aligned}
$$

$$
\begin{align*}
& -\int_{v_{1 /}}^{\left.S_{1} S_{1}-R_{1}\right)}\left[g\left(u^{\prime}-S_{1}^{\prime}-\mu^{\prime}\right)+g\left(u^{\prime}-S_{1}^{\prime}+\mu^{\prime}\right)\right] \cdot\left[G\left({ }^{v} 1 / u^{\prime}-S_{1}-\mu\right)+G\left({ }^{v} 1 / u^{\prime}-S_{1}+\mu\right)\right] d u^{\prime} . \tag{6.4}
\end{align*}
$$

Similarly,

$$
\iint_{D_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime}
$$

can be expressed explicitly as

$$
\begin{aligned}
& 1-\left[G\left({ }^{V_{2}} /\left(S_{2}{ }^{\prime}-R_{2}{ }^{\prime}\right)^{-S_{2}+\theta} 2^{-\mu}\right)+G\left({ }^{V_{2}} /\left(S_{2}{ }^{\prime}-R_{2}{ }^{\prime}\right)^{-S_{2}-\theta} 2^{+\mu}\right)\right] \cdot \\
& {\left[1-G\left(-R_{2}^{\prime}+\theta_{2}^{\prime}-\mu^{\prime}\right)-G\left(-R_{2}^{\prime}-\theta_{2}^{\prime}+\mu^{\prime}\right)\right]}
\end{aligned}
$$

$$
\begin{align*}
& -\int_{V_{2} /\left(S_{2}-R_{2}\right)}^{S_{2}^{\prime}-R_{2}^{\prime}}\left[g\left(u^{\prime}-S_{2}^{\prime}+\theta_{2}^{\prime-}-\mu^{\prime}\right)+g\left(u^{\prime}-S_{2}^{\prime}-\theta_{2}^{\prime}+\mu^{\prime}\right)\right] . \\
& {\left[G\left({ }^{\mathrm{V}} 2 / \mathrm{u}^{\prime}-\mathrm{S}_{2}+\theta_{2}-\mu\right)+G\left({ }^{\mathrm{V}} 2 / \mathrm{u}^{\prime}{ }^{-S_{2}-\theta} 2^{+\mu}\right)\right] d u^{\prime} .} \tag{6.5}
\end{align*}
$$

However, the term

$$
\int_{D_{1} \cap D_{2}} \int_{\mathrm{D}} \mathrm{f}\left(\mathrm{y}, \mathrm{y}^{\prime}\right) \mathrm{dy} d y^{\prime}
$$

in expression (6.3) is the one which causes a lot of trouble. The difficulty arises because there are so many possible shapes which the region $D_{1} \cap D_{2}$ may take that, a systematic treatment by a computer
program is almost impossible. In Figure 15 below, we give a few shapes that $D_{1} \cap D_{2}$ may assume:


Figure 15. Some Possible Shapes $D_{1} \cap D_{2}$ May Take.

To compound the problem, there are so many ways that we may or should partition the region "properly" that it is very hard to instruct a computer to do it. (The dotted lines in the above regions indicate a possible way of partitioning them.)

To be fair, the problem is not as difficult when the numerical values of the configuration are given. If we are given specific values of $T_{1}, T_{2}, P, \theta_{2}, \theta_{2}^{\prime}, \mu, \mu^{\prime}, v_{1}$ and $v_{2}$, then we can draw a diagram like the one in Figure 14, and partition the $D_{1} \cap D_{2}$ region properly
that we can integrate over it. Nevertheless, as far as computer programming is concerned, this approach again leads us nowhere.

Thus far, we have witnessed the collapse of two attemps to obtain a computer programmable formula for the joint c.d.f. of two rectangular coverages although in both cases "mathematical expressions" ((6.2), (6.3), and (6.3a)) were obtained for it. We shall take up this subject again in Chapter VIII. In the next chapter, we shall confine ourselves to the investigation of the joint probabilities of some "interesting" and 'useful' events. For example, the joint probability of hitting both targets, of missing both targets, of achieving the maximum possible coverage on both targets, etc.

## CHAPTER VII

## THE JOINT PROBABILITIES OF SOME <br> INTERESTING EVENTS

## 1. The Probability of Hitting Both Targets

Although in general we cannot obtain the joint probability of two rectangular coverages exactly, it is possible to find the exact joint probability of some "interesting" events such as the ones given in Questions (1) through (5) in Chapter I, Section 1. First, let us take Question (1) 'What is the probability of hitting both targets?'"

Around Target 1, we can construct a shaded rectangle (call it $\mathrm{K}_{1}$ ) such that when the pattern center lands inside it, we shall have some coverage on Target 1, and when the pattern center lands outside it, we shall have a complete miss on Target 1. Figure 16 shows the boundaries of this rectangle.

The marginal probabilities of hitting and missing Target 1 can be obtained as $\operatorname{Pr}($ hitting Target 1)

$$
\begin{align*}
=\iint_{K_{1}} f\left(y, y^{\prime}\right) d y d y^{\prime} & =\left[G\left(S_{1}-\mu\right)-G\left(-S_{1}-\mu\right)\right] \cdot\left[G\left(S_{1}^{\prime}-\mu^{\prime}\right)-G\left(-S_{1}^{\prime}-\mu^{\prime}\right)\right] \\
& =a \tag{7.1}
\end{align*}
$$

and
$\operatorname{Pr}($ missing Target 1$)=1-\mathrm{a}$.
(Note the closed form of these solutions)


Figure 16. The Rectangle Corresponding to the Fvent 'Hitting Target 1 "

Similarly, we can construct another shaded rectangle (call it $\mathrm{K}_{2}$ ) around Target 2 (with center at $\left(\theta_{2}, \theta_{2}^{\prime}\right)$ ). The marginal probabilities of hitting and missing Target 2 are:

Pr (hitting Target 2)
$\begin{aligned}=\iint_{K_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime}= & {\left[G\left(\theta_{2}+S_{2}-\mu\right)-G\left(\theta_{2}-S_{2}-\mu\right)\right] . } \\ & {\left[G\left(\theta_{2}^{\prime}+S_{2}^{\prime}-\mu^{\prime}\right)-G\left(\theta_{2}{ }^{\prime}-S_{2}^{\prime}-\mu^{\prime}\right)\right]=b }\end{aligned}$
and
$\operatorname{Pr}($ missing $\operatorname{Target} 2)=1-\mathrm{b}$.
Figure 17 shows both $K_{1}$ and $K_{2}$ on the same diagram.


Figure 17. The Rectangle Corresponding to the Event 'Hitting Both Targets'

From this diagram, it is not difficult to see that $\operatorname{Pr}(\text { hitting both targets })^{\prime}=\int_{K_{1} \cap K_{2}} \int_{\left(y, y^{\prime}\right) d y d y^{\prime} .}$

The expression given in (7.5) shall again give an answer in closed form. The actual expression for (7.5) depends on the way $K_{1}$ and $K_{2}$ intersect. A few examples are given in Figure 18.


Figure 18. Types of Intersection of the Sets $K_{1}$ and $K_{2}$

For each of the above intersections, the limits of integration for region $K_{1} \cap K_{2}$ are different. A way to exhaust all the possible ways of intersection is to consider the linear intersection for each of the range direction and the deflection direction first and then take the product.

Let us start with the intersection in the range direction. We note first that the extent of the boundary segment in the range direction is from $-S_{1}$ to $S_{1}$ for $K_{1}$, call this Segment 1 , and from $\theta_{2}-S_{2}$ to $\theta_{2}+S_{2}$ for $K_{2}$, call this Segment 2. For ease of discussion in what follows, let us define
$\mathrm{L}_{1}=-\mathrm{S}_{1} \quad$ (the "tail" of Segment 1 in the range direction)
$\mathrm{H}_{1}=\mathrm{S}_{1} \quad$ (the 'head' of Segment 1 in the range direction)
$\mathrm{L}_{2}=\theta_{2}-\mathrm{S}_{2}$ (the 'tail" of Segment 2 in the range direction)
$\mathrm{H}_{2}=\theta_{2}+\mathrm{S}_{2}$ (the 'head" of Segment 2 in the range direction). (7.6) Since both $S_{1}$ and $S_{2}$ are positive numbers, we have the following obvious relationships:

$$
\mathrm{L}_{1}<\mathrm{H}_{1} \text { and } \mathrm{L}_{2}<\mathrm{H}_{2}
$$

The definition given in (7.6) and the relationship among $L_{1}, H_{1}, L_{2}$, and $\mathrm{H}_{2}$ may make one recall Definition (4.4) and the relationship among $A_{1}, B_{1}, A_{2}$, and $B_{2}$ in Chapter IV. They are indeed closely related. As a matter of fact, $L_{1}, H_{1}, L_{2}$, and $H_{2}$ are special cases of $A_{1}, B_{1}, A_{2}$, and $B_{2}$ when $u_{1}=u_{2}=0$. Similar to expression (4.4a), we find the six ways Segment 1 and Segment 2 intersect to be:

1. $\mathrm{L}_{1} \leq \mathrm{L}_{2}<\mathrm{H}_{1} \leq \mathrm{H}_{2}$
2. $\mathrm{L}_{2} \leq \mathrm{L}_{1}<\mathrm{H}_{2} \leq \mathrm{H}_{1}$
3. $\mathrm{L}_{1}<\mathrm{H}_{1} \leq \mathrm{L}_{2}<\mathrm{H}_{2}$
4. $\mathrm{L}_{2}<\mathrm{H}_{2} \leq \mathrm{L}_{1}<\mathrm{H}_{1}$
5. $\mathrm{L}_{1} \leq \mathrm{L}_{2}<\mathrm{H}_{2} \leq \mathrm{H}_{1}$
6. $L_{2} \leq L_{1}<H_{1} \leq H_{2}$.

Corresponding to the six cases given in (7.7), the intersections are respectively:

1. $\left[L_{2}, H_{1}\right]=\left[\theta_{2}-S_{2}, S_{1}\right]$
2. $\left[\mathrm{L}_{1}, \mathrm{H}_{2}\right]=\left[-\mathrm{S}_{1}, \theta_{2}+\mathrm{S}_{2}\right]$
3. $\phi$
4. $\phi$
5. $\left[L_{2}, H_{2}\right]=\left[\theta_{2}-S_{2}, \theta_{2}+S_{2}\right]$
6. $\left[\mathrm{L}_{1}, \mathrm{H}_{1}\right]=\left[-\mathrm{S}_{1}, \mathrm{~S}_{1}\right]$.

The notation $[x, y]$ is understood as the closed interval from $x$ to $y$.
If we consider the linear intersection in the deflection direction, we shall have also six cases:

1. $\mathrm{L}_{1}^{\prime} \leq \mathrm{L}_{2}^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{H}_{2}^{\prime}$
2. $\mathrm{L}_{2}^{\prime} \leq \mathrm{L}_{1}^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$
3. $\mathrm{L}_{1}^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{L}_{2}^{\prime}<\mathrm{H}_{2}^{\prime}$
4. $\mathrm{L}_{2}^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{L}_{1}^{\prime}<\mathrm{H}_{1}^{\prime}$
5. $\mathrm{L}_{1}^{\prime} \leq \mathrm{L}_{2}^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$
6. $\mathrm{L}_{2}^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{H}_{2}^{\prime}$
where $L_{1}{ }^{\prime}, H_{1}^{\prime}, L_{2}^{\prime}$, and $H_{2}^{\prime}$ are defined similar to (7.6) but in the deflection direction. We shall have the respective intersection corresponding to (7.9) as
7. $\left[\mathrm{L}_{2}^{\prime}, \mathrm{H}_{1}{ }^{\prime}\right]=\left[\theta_{2}{ }^{\prime}-\mathrm{S}_{2}{ }^{\prime}, \mathrm{S}_{1}{ }^{\prime}\right]$
8. $\left[\mathrm{L}_{1}^{\prime}, \mathrm{H}_{2}^{\prime}\right]=\left[-\mathrm{S}_{1}, \theta_{2}^{\prime}+\mathrm{S}_{2}^{\prime}\right]$
9. $\phi$
10. $\phi$
11. $\left[\mathrm{L}_{2}^{\prime}, \mathrm{H}_{2}^{\prime}\right]=\left[\theta_{2}^{\prime}-\mathrm{S}_{2}^{\prime}, \theta_{2}^{\prime}+\mathrm{S}_{2}{ }^{\prime}\right]$
12. $\left[\mathrm{L}_{1}^{\prime}, \mathrm{H}_{1}^{\prime}\right]=\left[-\mathrm{S}_{1}^{\prime}, \mathrm{S}_{1}^{\prime}\right]$.

Now we can find product sets of the six cases in the range direction with the six cases in the deflection direction. The resultant 36 cases and the corresponding intersections are listed in TABLE I.

TABLE I
CASES OF $K_{1} \cap K_{2}$

| Case Number | Way of Intersecting in Range Direction | Way of Intersecting in Deflection Direction | The Resultant $K_{1} \cap K_{2}$ | Looks Like |
| :---: | :---: | :---: | :---: | :---: |
| 1 | $\mathrm{L}_{1}<\mathrm{L}_{2}<\mathrm{H}_{1}<\mathrm{H}_{2}$ | $\mathrm{L}_{1}{ }^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{1}{ }^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | $\begin{aligned} & {\left[\theta_{2}-S_{2}, S_{1}\right] x} \\ & {\left[\theta_{2}^{\prime}-S_{2}^{\prime}, S_{1}^{\prime}\right]} \end{aligned}$ | $k_{1}{ }^{k_{2}}$ |
| 2 | " | $L_{2}^{\prime} \leq L_{1}^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | $\begin{aligned} & {\left[\theta_{2}-S_{2}, S_{1}\right] x} \\ & {\left[-S_{1}^{\prime}, \theta_{2}^{\prime}+S_{1}^{\prime}\right]} \end{aligned}$ | $\sqrt{2}$ |
| 3 | " | $\mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{L}_{2}^{\prime}<\mathrm{H}_{2}^{\prime}$ | $\phi$ | (1) |
| 4 | " | $\mathrm{L}_{2}^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}^{\prime}$ | $\phi$ | 2] 1 |
| 5 | " | $\mathrm{L}_{1}^{\prime} \leq \mathrm{L}_{2}^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | $\begin{aligned} & {\left[\theta_{2}-S_{2}, S_{1}\right] x} \\ & {\left[\theta_{2}^{\prime}-S_{2}^{\prime}, \theta_{2}^{\prime}+S_{2}^{\prime}\right]} \end{aligned}$ | $\frac{2}{2}$ |
| 6 | " | $\mathrm{L}_{2}{ }^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | $\begin{aligned} & {\left[\theta_{2}-\mathrm{S}_{2}, \mathrm{~S}_{1}\right] \mathrm{x}} \\ & {\left[-\mathrm{S}_{1}^{\prime}, \mathrm{S}_{1}^{\prime}\right]} \end{aligned}$ | $\frac{1}{2}$ |
| 7 | $\mathrm{L}_{2} \leq \mathrm{L}_{1}<\mathrm{H}_{2} \leq \mathrm{H}_{1}$ | $\mathrm{L}_{1}{ }^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | $\begin{aligned} & {\left[-S_{1}, \theta_{2}+S_{2}\right] x} \\ & {\left[\theta_{2}^{\prime}-S_{2}^{\prime}, S_{1}^{\prime}\right]} \end{aligned}$ | $\stackrel{1}{4}$ |

(TABLE I continued)

| 8 | " | $\mathrm{L}_{2}{ }^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{2}{ }^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | $\begin{aligned} & {\left[-S_{1},\right.} \\ & \left.\theta_{2}+S_{2}\right] x \\ & {\left[-S_{1},\right.} \\ & \left.\theta_{2}+S_{2}^{\prime}\right] \end{aligned}$ | $2{ }^{1}$ |
| :---: | :---: | :---: | :---: | :---: |
| 9 | " | $\mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}{ }^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}^{\prime}$ | $\phi$ | 112 |
| 10 | " | $\mathrm{L}_{2}^{\prime}<\mathrm{H}_{2}{ }^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}^{\prime}$ | $\phi$ | [2] |
| 11 | " | $\mathrm{L}_{1}{ }^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | $\begin{aligned} & {\left[-S_{1}, \theta_{2}+S_{2}\right] x} \\ & {\left[\theta_{2}^{\prime}-S_{2}^{\prime}, \theta_{2}^{\prime}+S_{2}^{\prime}\right]} \end{aligned}$ | $\frac{1}{2}$ |
| 12 | " | $\mathrm{L}_{2}{ }^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | $\begin{gathered} {\left[-\mathrm{S}_{1},{ }_{2}+\mathrm{S}_{2}\right] \mathrm{x}} \\ {\left[-\mathrm{S}_{1}, \mathrm{~S}_{1}^{\prime}\right]} \end{gathered}$ | [ $\begin{gathered}\square \\ 2\end{gathered}$ |
| 13 | $\mathrm{L}_{1}<\mathrm{H}_{1} \leq \mathrm{L}_{2}<\mathrm{H}_{2}$ | $\mathrm{L}_{1}{ }^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{1}{ }^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | $\phi$ | $[\square$ |
| 14 | " | $\mathrm{L}_{2}^{\prime} \leq \mathrm{L}_{1}^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | $\phi$ | $\frac{[ }{I}$ |
| 15 | , " | $\mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}{ }^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}^{\prime}$ | $\phi$ | $[1]^{[2]}$ |
| 16 | " | $\mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}^{\prime}{ }^{\prime}$ | $\phi$ | B |
| 17 | " | $\mathrm{L}_{1}^{\prime} \leq \mathrm{L}_{2}^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | $\phi$ | $\frac{\square}{1}$ |
| 18 | " | $\mathrm{L}_{2}{ }^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}{ }^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | $\phi$ | E |
| 19 | $\mathrm{L}_{2}<\mathrm{H}_{2} \leq \mathrm{L}_{1}<\mathrm{H}_{1}$ | $\mathrm{L}_{1}{ }^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | $\phi$ | $\sqrt{1}$ |
| 20 | " | $\mathrm{L}_{2}{ }^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{2}{ }^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | $\phi$ | [1] |

(TABLE I continued)

| 21 | " | $\mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}{ }^{\prime}<\mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}^{\prime}$ | $\phi$ | [2 |
| :---: | :---: | :---: | :---: | :---: |
| 22 | " | $\mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{L}_{1}^{\prime}<\mathrm{H}_{1}^{\prime}$ | $\phi$ | [ |
| 23 | " | $\mathrm{L}_{1}{ }^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}{ }^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | $\phi$ | $\square$ |
| 24 | " | $\mathrm{L}_{2}{ }^{\prime}<\mathrm{L}_{1}^{\prime}<\mathrm{H}_{1}{ }^{\prime}<\mathrm{H}_{2}^{\prime}$ | $\phi$ | 1 <br> 2 |
| 25 | $\mathrm{L}_{1}<\mathrm{L}_{2}<\mathrm{H}_{2}<\mathrm{H}_{1}$ | $\mathrm{L}_{1}{ }^{\prime} \leq \mathrm{L}_{2}^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | $\begin{aligned} & {\left[\theta_{2}-S_{2}, \theta_{2}+S_{2}\right] x} \\ & {\left[\theta_{2}^{\prime}-S_{2}^{\prime}, S_{1}^{\prime}\right]} \end{aligned}$ | $172$ |
| 26 | " | $L_{2}{ }^{\prime} \leq L_{1}{ }^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | $\begin{array}{cc} {\left[\theta_{2}-S_{2},\right.} & \left.\theta_{2}+S_{2}\right] x \\ {\left[-S_{1}^{\prime},\right.} & \left.\theta_{2}^{\prime}+S_{2}^{\prime}\right] \end{array}$ | $\sqrt{21}$ |
| 27 | " | $\mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}^{\prime}$ | $\phi$ | $12$ |
| 28 | " | $\mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{L}_{1}^{\prime}<\mathrm{H}_{1}^{\prime}$ | $\phi$ | [24 |
| 29 | " | $\mathrm{L}_{1}{ }^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | Impossible Case | [5] |
| 30 | " | $\mathrm{L}_{2}{ }^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | Impossible Case | $\Psi^{3}$ |
| 31 | $\mathrm{L}_{2} \leq \mathrm{L}_{1}<\mathrm{H}_{1} \leq \mathrm{H}_{2}$ | $\mathrm{L}_{1}{ }^{\prime} \leq \mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | $\begin{aligned} & {\left[-\mathrm{S}_{1}, \mathrm{~S}_{1}\right] \mathrm{x}} \\ & {\left[\theta_{2}^{\prime}-\mathrm{S}_{2}^{\prime}, \mathrm{S}_{1}^{\prime}\right]} \end{aligned}$ | 12 |
| 32 | " | $\mathrm{L}_{2}{ }^{\prime} \leq \mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | $\begin{aligned} & {\left[-S_{1}, S_{1}\right] x} \\ & {\left[-S_{1}^{\prime}, \theta_{2}^{\prime}+S_{2}^{\prime}\right]} \end{aligned}$ | $\sqrt{271}$ |
| 33 | " | $\mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}{ }^{\prime}<\mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}{ }^{\prime}$ | $\phi$ | 回 |

## (TABLE I continued)

| 34 | " | $\mathrm{L}_{2}{ }^{\prime}<\mathrm{H}_{2}{ }^{\prime} \leq \mathrm{L}_{1}^{\prime}<\mathrm{H}_{1}^{\prime}$ | $\phi$ | 2] |
| :---: | :---: | :---: | :---: | :---: |
| 35 | " | $\mathrm{L}_{1}^{\prime} \leq \mathrm{L}_{2}^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime}$ | Impossible Case | 年 |
| 36 | " | $\mathrm{L}_{2}{ }^{\prime}<\mathrm{L}_{1}{ }^{\prime}<\mathrm{H}_{1}{ }^{\prime} \leq \mathrm{H}_{2}^{\prime}$ | Impossible Case | [迥 |

We now prove that Cases 29, 30, 35, ánd 36 are impossible.
Let us take Case 29 first. This case gives the way of intersection as:

$$
\mathrm{L}_{1} \leq \mathrm{L}_{2}<\mathrm{H}_{2} \leq \mathrm{H}_{1} \text { and } \mathrm{L}_{1}^{\prime} \leq \mathrm{L}_{2}^{\prime}<\mathrm{H}_{2}^{\prime} \leq \mathrm{H}_{1}^{\prime} .
$$

By definition, this is

$$
\begin{equation*}
-S_{1} \leq \theta_{2}-S_{2}<\theta_{2}+S_{2} \leq S_{1} \text { and }-S_{1}^{\prime} \leq \theta_{2}^{\prime}-S_{2}^{\prime}<\theta_{2}^{\prime}+S_{2}^{\prime} \leq S_{1}^{\prime} . \tag{7.11}
\end{equation*}
$$

The first inequality in (7.11) implies consecutively

$$
\begin{align*}
& -\mathrm{S}_{1} \leq \theta_{2}-\mathrm{S}_{2} \text { and } \theta_{2}+\mathrm{S}_{2} \leq \mathrm{S}_{1} \\
& -\mathrm{T}_{1}-\mathrm{P} \leq \theta_{2}-\mathrm{T}_{2}-\mathrm{P} \text { and } \theta_{2}+\mathrm{T}_{2}+\mathrm{P} \leq \mathrm{T}_{1}+\mathrm{P} \text { (by definition) } \\
& -\mathrm{T}_{1} \leq \theta_{2}-\mathrm{T}_{2} \text { and }{ }_{2}+\mathrm{T}_{2} \leq \mathrm{T}_{1} \\
& -\mathrm{T}_{1}<\theta_{2} \text { and } \theta_{2}<\mathrm{T}_{1} \quad \text { (since } \mathrm{T}_{2} \text { is positive) } \\
& \quad\left|\theta_{2}\right|<\mathrm{T}_{1} . \tag{7.12}
\end{align*}
$$

Similarly, the second inequality in (7.11) implies

$$
\begin{equation*}
\left|\theta_{2}^{\prime}\right|<\mathrm{T}_{1}^{\prime} . \tag{7.13}
\end{equation*}
$$

But (7.13) together with (7.12) means the center of Target 2 is inside Target 1 area, which is not allowed. Hence Case 29 is an impossible case.

Let us take Case 30 next. This case has an intersection given by:

$$
\mathrm{L}_{1} \leq \mathrm{L}_{2}<\mathrm{H}_{2} \leq \mathrm{H}_{1} \text { and } \mathrm{L}_{2}^{\prime} \leq \mathrm{L}_{1}^{\prime}<\mathrm{H}_{1}^{\prime} \leq \mathrm{H}_{2}^{\prime} \text {. }
$$

By definition, this is

$$
\begin{equation*}
-\mathrm{S}_{1} \leq \theta_{2}-\mathrm{S}_{2}<\theta_{2}+\mathrm{S}_{2} \leq \mathrm{S}_{1} \text { and } \theta_{2}^{\prime}-\mathrm{S}_{2}^{\prime} \leq-\mathrm{S}_{1}^{\prime}<\mathrm{S}_{1}^{\prime} \leq \theta_{2}^{\prime}+\mathrm{S}_{2}^{\prime} \tag{7.14}
\end{equation*}
$$

The first inequality in (7.14), as we have seen just a moment ago, implies

$$
\begin{equation*}
\left|\theta_{2}\right|<T_{1} . \tag{7.15}
\end{equation*}
$$

The second inequality in (7.14) implies, consecutively,

$$
\begin{align*}
& { }_{2}{ }^{\prime}-\mathrm{S}_{2}^{\prime} \leq-\mathrm{S}_{1}{ }^{\prime} \text { and } \mathrm{S}_{1}^{\prime} \leq \theta_{2}{ }^{\prime+}+\mathrm{S}_{2}{ }^{\prime} \\
& \theta_{2}{ }^{\prime}-\mathrm{T}_{2}^{\prime}-\mathrm{P}^{\prime} \leq-\mathrm{T}_{1}{ }^{\prime}-\mathrm{P} \text { and } \mathrm{T}_{1}^{\prime}+\mathrm{P} \leq \theta_{2}{ }^{\prime}+\mathrm{T}_{2}{ }^{\prime}+\mathrm{P} \quad \text { (by definition) } \\
& \theta_{2}^{\prime} \leq-\mathrm{T}_{1}^{\prime}+\mathrm{T}_{2}^{\prime} \text { and } \mathrm{T}_{1}{ }^{\prime}-\mathrm{T}_{2}^{\prime} \leq \theta_{2}^{\prime} \\
& { }^{\prime}{ }^{\prime}<\mathrm{T}_{1}^{\prime}+\mathrm{T}_{2}^{\prime} \text { and }-\mathrm{T}_{1}{ }^{\prime}-\mathrm{T}_{2}^{\prime}<\theta_{2}^{\prime} \quad \text { (since } \mathrm{T}_{1}^{\prime} \text { and } \mathrm{T}_{2}^{\prime} \text { are positive) } \\
& \quad\left|\theta_{2}^{\prime}\right|<\mathrm{T}_{1}{ }^{\prime}+\mathrm{T}_{2}{ }^{\prime} . \tag{7.16}
\end{align*}
$$

(7.16), together with (7.15), implies that the area of Target 1 and the area of Target 2 overlap like what is shown in Figure 19. This is again not allowed. Hence Case 30 is also an impossible case.

The impossibility of Case 35 can be proved by the same reasoning used for Case 30, and the impossibility of Case 36 can be proved in the same way as Case 29. It is just a matter of reversing Target 1 and Target 2.

Once the boundaries of $K_{1} \cap K_{2}$ are well defined in TABLE I for all possible cases, we can proceed to find the joint probability of hitting both targets. Let us define

$$
\mathrm{c}=\operatorname{Pr}(\text { hitting both targets) }
$$

From Expression (7.5) and TABLE I.we have the following results:


Figure 19. Targets Overlapping Implied by Case 30

Case 1: $c=^{\prime} \int_{K_{1} \cap K_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime}=\int_{\theta_{2}-S_{2}}^{S_{1}} f(y) d y \cdot \int_{\theta_{2}^{\prime}-S_{2}^{\prime}}^{S^{\prime}} f\left(y^{\prime}\right) d y^{\prime}$

$$
=\left[G\left(S_{1}-\mu\right)-G\left(\theta_{2}-S_{2}-\mu\right)\right] \cdot\left[G\left(S_{1}^{\prime}-\mu^{\prime}\right)-G\left(\theta_{2}^{\prime}-S_{2}^{\prime}-\mu^{\prime}\right)\right]
$$



$$
=\left[G\left(\mathrm{~S}_{1}-\mu\right)-\mathrm{G}\left(\theta_{2}-\mathrm{S}_{2}-\mu\right)\right] \cdot\left[\mathrm{G}\left(\theta_{2}^{\prime}+\mathrm{S}_{2}^{\prime}-\mu^{\prime}\right)-\mathrm{G}\left(-\mathrm{S}_{1}^{\prime}-\mu^{\prime}\right)\right]
$$

Case 5: $\mathrm{c}=\left[\mathrm{G}\left(\mathrm{S}_{1}-\mu\right)-\mathrm{G}\left(\theta_{2}-\mathrm{S}_{2}-\mu\right)\right] \cdot\left[\mathrm{G}\left(\theta_{2}^{\prime}+\mathrm{S}_{2}^{\prime}-\mu^{\prime}\right)-\mathrm{G}\left(\theta_{2}^{\prime}-\mathrm{S}_{2}^{\prime}-\mu^{\prime}\right)\right]$

Case 6: $\quad c=\left[G\left(S_{1}-\mu\right)-G\left(\theta_{2}-S_{2}-\mu\right)\right] \cdot\left[G\left(S_{1}^{\prime}-\mu^{\prime}\right)-G\left(-S_{1}^{\prime}-\mu^{\prime}\right)\right]$
Case 7: $\quad c=\left[G\left(\theta_{2}+S_{2}-\mu\right)-G\left(-S_{1}-\mu\right)\right] \cdot\left[G\left(S_{1}^{\prime}-\mu^{\prime}\right)-G\left(\theta_{2}^{\prime}-S_{2}^{\prime}-\mu^{\prime}\right)\right]$
Case 8: $\quad \mathbf{c}=\left[G\left(\theta_{2}+S_{2}-\mu\right)-G\left(-S_{1}-\mu\right)\right] \cdot\left[G\left(\theta_{2}^{\prime}+S_{2}^{\prime}-\mu^{\prime}\right)-G\left(-S_{1}^{\prime}-\mu^{\prime}\right)\right]$
Case 11: $c=\left[G\left(\theta_{2}+S_{2}-\mu\right)-G\left(-S_{1}-\mu\right)\right] \cdot\left[G\left(\theta_{2}^{\prime}+S_{2}^{\prime}-\mu^{\prime}\right)-G\left(\theta_{2}^{\prime}-S_{2}^{\prime}-\mu^{\prime}\right)\right]$

Case 12: $c=\left[G\left(\theta_{2}+S_{2}-\mu\right)-G\left(-S_{1}-\mu\right)\right] \cdot\left[G\left(S_{1}^{\prime}-\mu^{\prime}\right)-G\left(-S_{1}^{\prime}-\mu^{\prime}\right)\right]$

Case 25: $\mathbf{c}=\left[\mathrm{G}\left(\theta_{2}+\mathrm{S}_{2}-\mu\right)-\mathrm{G}\left(\theta_{2}-\mathrm{S}_{2}-\mu\right)\right] \cdot\left[\mathrm{G}\left(\mathrm{S}_{1}^{\prime}-\mu^{\prime}\right)-\mathrm{G}\left(\theta_{2}^{\prime}-\mathrm{S}_{2}^{\prime}-\mu^{\prime}\right)\right]$
Case 26: $\mathbf{c}=\left[G\left(\theta_{2}+S_{2}-\mu\right)-G\left(\theta_{2}-S_{2}-\mu\right)\right] \cdot\left[G\left(\theta_{2}^{\prime}+S_{2}^{\prime}-\mu^{\prime}\right)-G\left(-S_{1}^{\prime}-\mu^{\prime}\right)\right]$
Case 31: $\mathbf{c}=\left[G\left(S_{1}-\mu\right)-G\left(-S_{1}-\mu\right)\right] \cdot\left[G\left(S_{1}^{\prime}-\mu^{\prime}\right)-G\left(\theta_{2}^{\prime}-S_{2}^{\prime}-\mu^{\prime}\right)\right]$
Case 32: $\mathrm{c}=\left[\mathrm{G}\left(\mathrm{S}_{1}-\mu\right)-\mathrm{G}\left(-\mathrm{S}_{1}-\mu\right)\right] \cdot\left[\mathrm{G}\left(\theta_{2}^{\prime}+\mathrm{S}_{2}^{\prime}-\mu^{\prime}\right)-\mathrm{G}\left(-\mathrm{S}_{1}^{\prime}-\mu^{\prime}\right)\right]$.
$\mathrm{c}=0$ for cases $3,4,9,10,13,14,15,16,17,18,19,20,21,22,23$, $24,27,28,33$, and 34 . Case $29,30,35$, and 36 are impossible cases. We shall call all the above expressions of $c$ collectively as formula (7.17)

## 2. A Two-way Table to Find Probabilities of Some Other Interesting Events

The joint probability of hitting both targets which we obtained in formula (7.17), together with the marginal probabilities expressed in (7.1), (7.2), (7.3), and (7.4), will enable us to also answer the following questions easily:
(2) What is the probability of hitting Target 1 but missing Target 2?
(3) What is the probability of hitting Target 2 but missing Target 1?
(4) What is the probability of missing both targets?

Before answering these questions, we recall that, in expression (7.1) and (7.3), we have

$$
\begin{aligned}
\mathrm{a} & =\operatorname{Pr}(\text { hitting Target 1) } \\
& =\left[G\left(\mathrm{~S}_{1}-\mu\right)-G\left(-\mathrm{S}_{1}-\mu\right)\right] \cdot\left[G\left(\mathrm{~S}_{1}^{\prime}-\mu^{\prime}\right)-G\left(-\mathrm{S}_{1}^{\prime}-\mu^{\prime}\right)\right], \text { and } \\
\mathrm{b} & =\operatorname{Pr}(\text { hitting Target } 2) \\
& =\left[G\left(\theta_{2}+S_{2}-\mu\right)-G\left(\theta_{2}-\mathrm{S}_{2}-\mu\right)\right] \cdot\left[G\left(\theta_{2}^{\prime}+\mathrm{S}_{2}^{\prime}-\mu^{\prime}\right)-G\left(\theta_{2}^{\prime}-\mathrm{S}_{2}^{\prime}-\mu^{\prime}\right)\right] .
\end{aligned}
$$

$\Lambda$ two-way table can be constructed in the following way: we first enter the joint probability of hitting both targets, the marginal probabilities of hitting and missing Target 1 , and the marginal probabilities of hitting and missing Target 2 in the table. The remaining three cells then can be filled in by using the principle that the sum of the row entries equals to the row margin and the sum of the column entries equals to the column margin. The circled values in Figure 20 are filled in by using this principle.

Target 2


Figure 20. A Two-way Table of Joint Probabilities

Question (2), (3), and (4) are then answered by (a-c), (b-c), and (1-a-b+c) respectively. We note that all the answers are in closed form since $a, b$, and $c$ are all in closed form. Figure 21 below shows a two-way table with numerical values as an example:

Target 2


Figure 21. A Two - way Table with Numerical Values

## 3. An Extention of the Two-way Table Method

The Two-way Table Method illustrated in the last section may also be extended to the case of n rectangular patterns, identical* or nonidentical. As usual, we assume that all pattern landing points are distributed independently.

Let us consider the case of n identical patterns first. The probability that all n patterns miss Target 1 is the product of the probabilities of Pattern 1 missing Target 1, Pattern 2 missing Target 1, $\ldots$, and Pattern $n$ missing Target 1. This is nothing but $(1-a)^{n}$. Similarly, we shall have
$\operatorname{Pr}($ all n patterns missing Target 2$)=(1-\mathrm{b})^{\mathrm{n}}$, and
$\operatorname{Pr}(a 11 \mathrm{n}$ patterns missing both targets $)=(1-a-b+c)^{\mathrm{n}}$
Thus the two-way table corresponding to the n identical patterns can be constructed by entering these three values first. Figure 22 gives an illustration. Again the circled values are filled in by using the "sum equals the margin" principle. We note that the probability in the 'Hitting-Hitting" cell in Figure 22 is the probability that Target 1 is hit by at least one of the $n$ patterns and Target 2 is hit by at least one of the $n$ patterns.

When we have n non-identical patterns, the procedure is more tedious. We have to construct a two-way table for each pattern. Figure 23 shows such a table for the ith pattern.

[^2]

Figure 22, A Two-way Table for n Identical Patterns


Figure 23. A Two-way Table for the $i \frac{\text { th }}{}$ Non-identical Pattern

Thus, for $\mathrm{i}=1,2, \ldots, \mathrm{n}$, we have n two-way tables, each is like the one above. We note that, in general, $a_{i} \neq a_{j}, b_{i} \neq b_{j}$, and $c_{i} \neq c_{j}$ for $i \neq j$.

A reasoning similar to the one we used to obtain the two-way table in Figure 22 will lead us to the construction of the two-way table for $n$ non-identical patterns. The two-way table given in Figure 24 results.

Target 2


Figure 24. A Two-way Table for n Non-identical Patterns

To summarize Sections 2 and 3 of this chapter, we have developed a procedure, the so called ''Two-way Table Method'', which enables us to answer Question (1), (2), (3), and (4), specified in Section 1 of Chapter 1 , for n identical or non-identical patterns by merely using formulas (7.1), (7.3), and (7.17).
4. The Fewest Number of Passes Required to Achieve a Specified Probability of Hitting Both Targets

Suppose we have identical rectangular patterns delivered on two rectangular targets. Another interesting question one may ask is, 'What is the fewest number of passes required to have a probability of at least, say 0.9 of hitting both targets?' The answer to this question turns out to be rather easy to find. We first obtain values for a, b, and c from Formulas (7.1), (7.3), and (7.17), respectively. Once this is done, we use the expression in the 'Hitting-Hitting' cell of the two-way table in Figure 22 and obtain the following inequality:

$$
\begin{equation*}
1-(1-a)^{n}-(1-b)^{n}+(1-a-b+c)^{n} \geq 0.9 \tag{7.18}
\end{equation*}
$$

Since the values of $a, b$, and $c$ are known, the smallest value of $n$ which satisfies the inequality in (7.18) can be found using a simple iterative procedure.

If we do not know $c$, the joint probability of hitting both targets, and use the product of marginal probabilities, $a \cdot b$, to estimate $c$, what would happen to the calculation of the $n$ value? The answer is that we may sometimes over estimate it and sometimes under estimate it Consider inequality (7.19) below:

$$
\begin{equation*}
1-(1-a)^{n}-(1-b)^{n}+(1-a-b+a b)^{n} \geq 0.9 \tag{7.19}
\end{equation*}
$$

This is an inequality we could use to calculate $n$ were $c$ not available. When $a \cdot b$ is greater than $c$, the $n$ value obtained from (7.19) will be smaller than the true $n$ value. On the other hand, when $a \cdot b$ is
smaller than $c$, the $n$ value obtained from (7.19) will be greater than the true $n$ value. This is true since $(1-a-b+x)^{n}$ is a monotone increasing function of x .

Another related question is the following. Does the fact that an n value that satisfies both $\operatorname{Pr}$ (hitting Target 1 ) $\geq 0.9$ and $\operatorname{Pr}($ hitting Target 2$) \geq 0.9$ imply that this $n$ value will also satisfy $\operatorname{Pr}$ (hitting both targets) $\geq 0.9$ ? The answer is no. The relationship between the joint probability and its two marginal probabilities is
$\operatorname{Pr}($ hitting both targets $)<\min [\operatorname{Pr}($ hitting Target 1), $\operatorname{Pr}($ hitting Target 2)]

The reason for the strict inequality is that we theoretically have no zero values in the Hitting-Missing and Missing-Hitting ce11s in the two-way table in Figure 22. As a consequence of this inequality, the n value which satisfies both $\operatorname{Pr}$ (hitting Target 1) $\geq 0.9$ and $\operatorname{Pr}($ hitting Target 2$) \geq 0.9$ is, in general, an under estimate of the true $n$ value which satisfies $\operatorname{Pr}$ (hitting both targets) $\geq 0.9$.

One last comment: Everything developed so far in this chapter is applicable to point targets. A point target is a special case of rectangular target when $T=T^{\prime}=0$.
5. The Probability of Achieving the

Maximum Possible Coverage on Both Targets

In this section, we shall answer Question (5) given in Chapter I, Section 1, namely, 'What is the probability of achieving the maximum possible coverage on both targets?" When a rectangular pattern is delivered on two rectangular targets, the maximum possible coverage on

Target 1, call it MPC1, is given by

$$
\begin{equation*}
\operatorname{MPCL}=\min \left(2 \mathrm{~T}_{1}, 2 \mathrm{P}\right) \cdot \min \left(2 \mathrm{~T}_{1}^{\prime}, 2 \mathrm{P}^{\prime}\right)=\left(\mathrm{S}_{1}-\mathrm{R}_{1}\right) \cdot\left(\mathrm{S}_{1}^{\prime}-\mathrm{R}_{1}^{\prime}\right) \tag{7.20}
\end{equation*}
$$

This relationship is implied in Gay and Weeks (1973). The probability of achieving MPC1 may be found as follows:

$$
\begin{align*}
\operatorname{Pr}[\text { achieving MPC1 }] & =\operatorname{Pr}\left[Z=\left(S_{1}-R_{1}\right) \cdot\left(S_{1}^{\prime}-R_{1}^{\prime}\right)\right]=\operatorname{Pr}\left[\left(Y, Y^{\prime}\right) \varepsilon J_{1}\right] \\
= & \iint_{J_{1}} f\left(y, y^{\prime}\right) d y d y^{\prime} \tag{7.21}
\end{align*}
$$

where region $J_{1}$ is defined in Figure 25.


Figure 25. The Region Corresponding to the Event "Achieving MPC1"

We note the similarity between the boundaries of $J_{1}$ and the boundaries of $K_{1}$ defined in Figure 16. As a matter of fact, both are 1imits of the boundaries of the region $D$ defined in Figure 13. If we set $\left(\theta, \theta^{\prime}\right)=(0,0)$ in Figure 13, then it is not difficult to verify that $K_{1}$ is the limit of $D$ when $v \rightarrow 0$, and $J_{1}$ is the limit of $D$ when $\mathrm{v} \rightarrow\left(\mathrm{S}_{1}-\mathrm{R}_{1}\right) \cdot\left(\mathrm{S}_{1}^{\prime}-\mathrm{R}_{1}^{\prime}\right)$. Using these as the boundaries of $\mathrm{J}_{1}$ in (7.21), we have:

$$
\begin{aligned}
\operatorname{Pr}[\text { achieving MPC1] } & =\int_{-R_{1}}^{R_{1}} f(y) d y \cdot \int_{-R_{1}^{\prime}}^{R_{1}^{\prime}} f\left(y^{\prime}\right) d y^{\prime} \\
& =\left[G\left(R_{1}-\mu\right)-G\left(-R_{1}-\mu\right)\right] \cdot\left[G\left(R_{1}^{\prime}-\mu^{\prime}\right)-G\left(-R_{1}^{\prime}-\mu^{\prime}\right)\right]
\end{aligned}
$$

By the same token, we can construct a region $\mathrm{J}_{2}$ for Target 2 and find

$$
\begin{aligned}
\operatorname{Pr}[\text { achieving MPC2] }= & \iint_{J_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime}=\int_{\theta_{2}-R_{2}}^{\theta} 2^{+R_{2}} f(y) d y \cdot \\
& \int_{\theta_{2}}^{\theta} 2^{\prime+R_{2}}{ }^{\prime} f\left(y^{\prime}\right) d y^{\prime} \\
& =\left[G\left(\theta_{2}+R_{2}-\mu\right)-G\left(\theta_{2}-R_{2}-\mu\right)\right] \cdot\left[G\left(\theta_{2}^{\prime}+R_{2}^{\prime}-\mu^{\prime}\right)-G\left(\theta_{2}^{\prime}-R_{2}^{\prime}-\mu^{\prime}\right)\right]
\end{aligned}
$$

where $\left(\theta_{2}, \theta_{2}\right)$ is the center of Target 2.
Consider now the intersection $J_{1} \cap J_{2}$ of the regions $J_{1}$ and $J_{2}$. This $J_{1} \cap J_{2}$ region is the one which, when we integrate $f\left(y, y^{\prime}\right)$ over it, will give us the probability of achieving the maximum coverage on both targets. Figure 26 shows $J_{1}, J_{2}$, and $J_{1} \cap J_{2}$.


Figure 26. The Region Corresponding to the Event
"Achieving MPC on Both Targets"

Thus,

$$
\begin{equation*}
\operatorname{Pr}(\text { achieving MPC on both targets })=\int_{J_{1} \cap J_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime} \tag{7.22}
\end{equation*}
$$

The problem again amounts to finding the correct boundaries for the region $J_{1} \cap J_{2}$.

Although we could have followed the same route in finding $K_{1} \cap K_{2}$ in Section 1 of this chapter, working things out case by case, we would like to try a different and better approach here.

Let us define

$$
\begin{align*}
& \mathrm{x}=\max \left(-R_{1}, \theta_{2}-R_{2}\right),  \tag{7.23}\\
& \mathrm{w}=\min \left(\mathrm{R}_{1}, \theta_{2}+R_{2}\right),  \tag{7.24}\\
& \mathrm{OP}=\text { Overlap of } J_{1} \text { and } J_{2} \text { in the range direction, }  \tag{7.25}\\
& \text { then }  \tag{7.26}\\
& \mathrm{OP}= \begin{cases}{[x, w]} & \text { if } w-x>0 \\
0 & \text { if } w-x \leq 0\end{cases}
\end{align*}
$$

where [ $\mathrm{x}, \mathrm{w}$ ] is understood to be the closed interval from x to w .
Similarly, if we define

$$
\begin{align*}
& \mathrm{x}^{\prime}=\max \left(-\mathrm{R}_{1}^{\prime}, \theta_{2}^{\prime}-\mathrm{R}_{2}^{\prime}\right),  \tag{7.27}\\
& \mathrm{w}^{\prime}=\min \left(\mathrm{R}_{1}^{\prime}, \theta_{2}^{\prime}+\mathrm{R}_{2}^{\prime}\right),  \tag{7.28}\\
& \mathrm{OP}^{\prime}=\text { Overlap of } J_{1} \text { and } J_{2} \text { in the deflection direction, } \tag{7.29}
\end{align*}
$$

then $O P= \begin{cases}{\left[x^{\prime}, w^{\prime}\right]} & \text { if } w^{\prime}-x^{\prime}>0 \\ 0 & \text { if } w^{\prime}-x^{\prime} \leq 0 .\end{cases}$
The intersection of $J_{1}$ and $J_{2}$ is the product of the overlap of $J_{1}$ and $J_{2}$ in the range direction and the overlap of $J_{1}$ and $J_{2}$ in the deflection direction. Thus, expression (7.22) becomes

$$
\begin{align*}
& \operatorname{Pr}(\text { achieving MPC on both targets })=\int_{J_{1} \cap \int_{J_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime}}=\int_{O P x O P^{\prime}} \int_{x^{\prime}} f\left(y, y^{\prime}\right) d y d y^{\prime} \\
& = \begin{cases}\int_{x}^{w} f(y) d y \cdot \int_{x^{\prime}}^{w^{\prime}} f\left(y^{\prime}\right) d y^{\prime}=[G(w-\mu)-G(x-\mu)] \cdot\left[G\left(w^{\prime}-\mu^{\prime}\right)-G\left(x^{\prime}-\mu^{\prime}\right)\right] \\
0 & \text { if w-x>0 and } w^{\prime}-x^{\prime}>0 \\
\text { otherwise }\end{cases}
\end{align*}
$$

where $w, x, w^{\prime}$, and $x^{\prime}$ are defined in (7.23), (7.24), (7.27), and (7.28) respectively. Again we have a closed form answer for Question (5).

Thus we have answered Questions (1) through (5) which are stated in Chapter I, Section 1. The 'Two-way Table Method" is a handy device with which to obtain answer to Questions (2), (3), (4) by using the answer to Question (1).

In the next chapter, we are going to continue the unfinished task left from Chapter VI and given an approximation of the joint c.d.f. of two rectangular coverages.

CHAPTER VIII

AN APPROXIMATION OF THE JOINT C.D.F. OF TWO RECTANGULAR COVERAGES

Recall that the main obstacle we encountered in trying to obtain the joint c.d.f. there, was the shape of the intersection of regions $D_{1}$ and $\mathrm{D}_{2}$ as illustrated in Figure 14. The difficulty arises because of the curved portions of the boundaries of $D_{1}$ and $D_{2}$.

Now suppose we approximate both $\mathrm{D}_{1}$ and $\mathrm{D}_{2}$ with rectangular regions by removing the curve from each of the four corners and extending the four boundary segments on each. To illustrate this, we reproduce Figure 14 with the proposed approximations shown in Figure 27. We note that the intersection of these two rectangular approximations is a rectangle too. This is the reason why we choose the rectangular approximation.

Now let the rectangular approximations of $D_{1}$ and $D_{2}$ be denoted by $\mathrm{D}_{1} *$ and $\mathrm{D}_{2}{ }^{*}$ respectively. The approximation we propose is to evaluate

$$
\begin{align*}
& \iint_{D_{1} \cap D_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime}  \tag{8.1}\\
\text { by } \quad & \int_{D_{1}^{*} \cap \cap_{D_{2}^{*}}} f\left(y, y^{\prime}\right) d y d y^{\prime} . \tag{8.2}
\end{align*}
$$


Figure 27. Approximating $\mathrm{D}_{1}$ and $\mathrm{D}_{2}$ by Two Rectangles

This in turn implies that the joint c.d.f. of two rectangular coverages expressed in (6.3) is approximated by $F_{Z_{1}}^{*}, Z_{2}\left(v_{1}, v_{2}\right)$ as follows:

$$
\begin{align*}
& F_{z_{1}}^{*}, Z_{2}\left(v_{1}, v_{2}\right)=1- {\left[\iint_{D_{1}} f\left(y, y^{\prime}\right) d y d y^{\prime}+\iint_{D_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime}\right.} \\
&-\int_{D_{1} * \cap D_{1} *} \int_{1} f\left(y, y^{\prime}\right) d y d y^{\prime} \\
& \text { for } 0 \leq v_{1}<\left(S_{1}-R_{1}\right)\left(S_{1}^{\prime}-R_{1}^{\prime}\right) \text { and } \\
& 0 \leq v_{2}<\left(S_{2}-R_{2}\right)\left(S_{2}^{\prime}-R_{2}^{\prime}\right) \tag{8.3}
\end{align*}
$$

The terms

$$
\iint_{D_{1}} f\left(y, y^{\prime}\right) d y d y^{\prime} \text { and } \iint_{D_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime}
$$

have been expressed explicitly in (6.4) and (6.5). As for the last term in (8.3), the integration is performed over the intersection of the two rectangles. By using the same approach we used to obtain (7.31) in Chapter VII, Section 5, we find that

$$
\int_{D_{1}^{*} \cap D_{2}^{*}} f\left(y, y^{\prime}\right) d y d y^{\prime}=\left\{\begin{array}{l}
{[G(Q-\mu)-G(E-\mu)] \cdot\left[G\left(Q^{\prime}-\mu^{\prime}\right)-G\left(E^{\prime}-\mu^{\prime}\right)\right]} \\
0 \\
\text { if } Q-E>0 \text { and } Q^{\prime}-E^{\prime}>0
\end{array}\right.
$$

where $E=\max \left(-S_{1}+{ }^{v_{1}} / S_{S^{\prime}}-R_{1}{ }^{\prime},{ }_{2}-S_{2}+{ }^{v_{2}} / S_{2}{ }^{\prime}-R_{2}{ }^{\prime}\right)$
$\mathrm{Q}=\min \left(\mathrm{S}_{1}-{ }^{\mathrm{v}_{1}} / \mathrm{S}_{1}{ }^{\prime}-\mathrm{R}_{1}{ }^{\prime},{ }^{\theta_{2}}+\mathrm{S}_{2}-{ }^{v_{2}} /_{S_{2}}{ }^{\prime}-\mathrm{R}_{2}{ }^{\prime}\right)$
$E^{\prime}=\max \left(-\mathrm{S}_{1}{ }^{\prime+}{ }^{v_{1}} / \mathrm{S}_{1}-\mathrm{R}_{1}, \theta_{2}{ }^{\prime}-\mathrm{S}_{2}{ }^{\prime}+\mathrm{V}_{2} / \mathrm{S}_{2}-\mathrm{R}_{2}\right)$
and

$$
Q^{\prime}=\min \left(S_{1}^{\prime}-v_{1 / S_{1}-R_{1}}, \theta_{2}^{\prime}+S_{2}^{\prime}-v_{2 /} S_{2}-R_{2}\right)
$$

Thus, the substitution of (8.4) into (8.3) will give us the approximation part of the c.d.f. of two rectangular coverages. This, together with the exact part of the c.d.f. expressed in (6.3a), gives us the following:
$F_{z_{1}}^{*}, Z_{2}\left(v_{1}, v_{2}\right)$

where $E, Q, E^{\prime}$, and $Q^{\prime}$ are as defined in (8.4).

We note that

$$
F_{z_{1}}^{*}, z_{2}\left(v_{1}, v_{2}\right) \geq F_{z_{1}, z_{2}}\left(v_{1}, v_{2}\right)
$$

This approximation, in our opinion, is on the right side of the true value, since the event " $Z_{1} \leq v_{1}$ and $z_{2} \leq v_{2}$ " is an undesirable event and it is safer to over estimate the probability of an undesirable event than to under estimate it.

It may happen that we are more interested in the joint probability of covering at least a certain area of Target 1 and covering at least a certain area of Target 2. This means that instead of $\operatorname{Pr}\left(z_{1} \leq v_{1}, z_{2} \leq v_{2}\right), \operatorname{Pr}\left(z_{1} \geq v_{1}, z_{2} \geq v_{2}\right)$ is the thing that is more useful for us to find, like Question (6) given in Chapter 1, Section 1. This probability is evaluated by expression (8.1) and approximated by expression (8.2) for $0<v_{1} \leq\left(S_{1}-R_{1}\right)\left(S_{1}^{\prime}-R_{1}^{\prime}\right)$ and $0<v_{2} \leq\left(S_{2}-R_{2}\right)\left(S_{2}^{\prime}-R_{2}^{\prime}\right)$. For $\left(v_{1}, v_{2}\right)$ not belonging to this region, the probability can be obtained in exact form. Together, the following formula gives us an approximation:

$$
\begin{align*}
& \operatorname{Pr}\left(Z_{1} \geq v_{1}, z_{2} \geq v_{2}\right) \\
& \left\{\begin{array}{l}
{[G(Q-\mu)-G(E-\mu)] \cdot\left[G\left(Q^{\prime}-\mu^{\prime}\right)-G\left(E^{\prime}-\mu^{\prime}\right)\right]} \\
\text { for } 0<v_{1} \leq\left(S_{1}-R_{1}\right)\left(S_{1}^{\prime}-R_{1}^{\prime}\right) \text { and } 0<v_{2} \leq\left(S_{2}-R_{2}\right)\left(S_{2}^{\prime}-R_{2}^{\prime}\right) \\
\text { and if } Q-E>0 \text { and } Q^{\prime}-E^{\prime}>0 \\
0 \text { for } 0<v_{1} \leq\left(S_{1}-R_{1}\right)\left(S_{1}^{\prime}-R_{1}^{\prime}\right) \text { and } 0<v_{2} \leq\left(S_{2}-R_{2}\right)\left(S_{2}^{\prime}-R_{2}^{\prime}\right) \\
\text { and if } Q-E \leq 0 \text { or } Q^{\prime}-E^{\prime} \leq 0 \\
\iint_{1} f\left(y, y^{\prime}\right) \text { dy dy' } \\
\text { for } 0<v_{1} \leq\left(S_{1}-R_{1}\right)\left(S_{1}^{\prime}-R_{1}^{\prime}\right) \text { and } v_{2} \leq 0 \\
\iint_{D} f\left(y, y^{\prime}\right) \text { dy dy } \\
\text { for } v_{1} \leq 0 \text { and } 0<v_{2} \leq\left(S_{2}-R_{2}\right)\left(S_{2}^{\prime}-R_{2}^{\prime}\right) \\
1 \text { for } v_{1} \leq 0 \text { and } v_{2} \leq 0 \\
0 \text { for } v_{1}>\left(S_{1}-R_{1}\right)\left(S_{1}^{\prime}-R_{1}^{\prime}\right) \text { or } v_{2}>\left(S_{2}-R_{2}\right)\left(S_{2}^{\prime}-R_{2}^{\prime}\right) \text { (8.6) }
\end{array}\right.
\end{align*}
$$

Again, $\operatorname{Pr}^{*}\left(z_{1} \geq v_{1}, z_{2} \geq v_{2}\right) \geq \operatorname{Pr}\left(z_{1} \geq v_{1}, z_{2} \geq v_{2}\right)$. However, this approximation is on the wrong side of the true value. Since the event ' $z_{1} \geq v_{1}$ and $z_{2} \geq v_{2}$ " is a desirable event.

To conclude, we have given approximations to both the joint c.d.f. of two rectangular coverages and the joint probability of the event $' z_{1} \geq v_{1}$ and $z_{2} \geq v_{2} . "$

## CHAPTER IX

## EXTENTION TO M RECTANGULAR TARGETS

The results obtained in all the previous chapters can be extended to the case of $m$ targets ( $m>2$ ). This is possible due to the approach we developed in finding the intersection of two rectangles in Chapter VII, Section 5. For example, consider the case where a rectangular pattern is delivered on three rectangular targets. The probability of hitting all three targets can be obtained by integrating $f\left(y, y^{\prime}\right)$ over the intersection of $K_{1}, K_{2}$, and $K_{3}$ as shown on the diagram in Figure 28. $\left(\theta_{3}, \theta_{3}\right)$ there is the center of Target 3 and $S_{3}=T_{3}+P, S_{3}^{\prime}=T_{3}{ }^{\prime+P^{\prime}}$. We note that the diagram in Figure 28 is an extension of the diagram in Figure 17.

The intersection, $K_{1} \cap \mathrm{~K}_{2} \cap \mathrm{~K}_{3}$, is a rectangle again. This rectangle is the product of the overlap of the three segments in the range direction and the overlap of the three segments in the deflection direction. In the range direction, the three segments involved are $\left[-\mathrm{S}_{1}\right.$, $\left.S_{1}\right],\left[\theta_{2}-S_{2}, \theta_{2}+S_{2}\right]$, and $\left[\theta_{3}-S_{3}, \theta_{3}+S_{3}\right]$. To find the overlap of them, we follow the method we used in Chapter VII, Section 5 and define

$$
\begin{align*}
& \forall=\max \left(-S_{1}, \theta_{2}-S_{2}, \theta_{3}-S_{3}\right), \text { and } \\
& \dot{Y}=\min \left(S_{1}, \theta_{2}+S_{2}, \theta_{3}+S_{2}\right) . \tag{9.1}
\end{align*}
$$

If we le the overlap in the range direction be denoted by $O P$, then

$$
\mathrm{OP}=\left\{\begin{array}{cl}
[\nexists, \gamma]] & \text { if } \dot{\gamma}-\ngtr>0  \tag{9.2}\\
0 & \text { otherwise } .
\end{array}\right.
$$



Figure 28. The Rectangle Corresponding to the Event 'Hitting A11 Three Targets"

Similarly, we can obtain the overlap of the three segments in the deflectimon direction, $\left[-\mathrm{S}_{1}{ }^{\prime}, \mathrm{S}_{1}{ }^{\prime}\right],\left[\theta_{2}{ }^{\prime}-\mathrm{S}_{2}{ }^{\prime}, \theta_{2}{ }^{\prime}+\mathrm{S}_{2}{ }^{\prime}\right]$ and $\left[\theta_{3}{ }^{\prime}-\mathrm{S}_{3}{ }^{\prime}, \theta_{3}{ }^{\prime}+\mathrm{S}_{3}{ }^{\prime}\right]$, as

$$
O P^{\prime}=\left\{\begin{array}{cl}
{\left[\mathcal{X}^{\prime}, \beta^{\prime}\right]} & \text { if } \gamma^{\prime}-x^{\prime}>0  \tag{9.3}\\
0 & \text { otherwise }
\end{array}\right.
$$

where $\mathcal{X}^{\prime}$ and ${ }^{\prime \prime}$ 'are defined as the counterparts of $\notin$ and $\mathfrak{\gamma}$ for the deflection direction. Thus we find
$K_{1} \cap K_{2} \cap K_{3}=O P . x^{\prime}{ }^{\prime}$

$$
= \begin{cases}{[x, q]_{x}\left[x^{\prime}, \gamma^{\prime}\right]} & \text { if } \hat{\gamma}-x>0 \text { and } p^{\prime}-x^{\prime}>0 \\ 0 & \text { otherwise. }\end{cases}
$$

Returning to our original problem, we find


The nice thing about this approach is that it can be easily extended to any number of targets. In the general case of $m$ targets, we only have to redefine

$$
\begin{align*}
* & =\max \left(-S_{1}, \theta_{2}-S_{2}, \ldots \theta_{m}-S_{m}\right) \\
Y & =\min \left(S_{1}, \theta_{2}+S_{2}, \ldots \theta_{m}+S_{m}\right) . \tag{9.5}
\end{align*}
$$

The rest of the derivation is exactly the same and we still end up with formula (9.4) as $\operatorname{Pr}$ (hitting all m targets).

We recall that the $\operatorname{Pr}$ (achieving MPC on both targets) in Chapter VII,

Section 5, and the approximation of the $\operatorname{Pr}\left(z_{1} \geq v_{1}, z_{2} \geq v_{2}\right)$ in Chapter VIII were both obtained by integrating $f\left(y, y^{\prime}\right)$ over the intersection of two rectangles. In the case of $m$ rectangular targets, the problem also amounts to finding the intersection of $m$ rectangles, the mechanism of which has been illustrated above. Once the intersection, always a rectangle, is found, the integration over it causes no difficulty.

To extend the approximation of the joint c.d.f. of rectangular coverages from two to m targets is a little bit more tedious, but still feasible. We shall illustrate it by first considering $m=3$. Similar to the diagram in Figure 27, we shall this time have $D_{1}, D_{2}$, and $D_{3}$. The exact joint c.d.f. is expressed in the following formula:

$$
\begin{align*}
& F\left(v_{1}, v_{2}, v_{3}\right)=\operatorname{Pr}\left(z_{1} \leq v_{1}, z_{2} \leq v_{2}, z_{3} \leq v_{3}\right) \\
& =1-\int_{D_{1} \cup D_{2} \cup D_{3}} f\left(y, y^{\prime}\right) d y d y^{\prime} . \tag{9.6}
\end{align*}
$$

The 'Principle of Inclusion and Exclusion", can be used to express the union, $D_{1} \cup D_{2} \cup D_{3}$, as the sum of intersections. That is

$$
\begin{equation*}
\mathrm{D}_{1} \cup \mathrm{D}_{2} \cup \mathrm{D}_{3}=\mathrm{D}_{1}+\mathrm{D}_{2}+\mathrm{D}_{3}-\left(\mathrm{D}_{1} \cap \mathrm{D}_{2}\right)-\left(\mathrm{D}_{1} \cap \mathrm{D}_{3}\right)-\left(\mathrm{D}_{2} \cap \mathrm{D}_{3}\right)+\left(\mathrm{D}_{1} \cap \mathrm{D}_{2} \cap \mathrm{D}_{3}\right) \tag{9.7}
\end{equation*}
$$

where the symbol " + " and "-" are defined in Berman and Fryer (1972, pp. 60-61). For examp1e, $A+B$ represents the totality of elements in $A$ and $B$ (with repeats counted).

There are at least two approximations we can use for (9.7):
(1) $\mathrm{D}_{1}{ }^{*}+\mathrm{D}_{2}{ }^{*}+\mathrm{D}_{3}{ }^{*}-\left(\mathrm{D}_{1}{ }^{*} \cap \mathrm{D}_{2}{ }^{*}\right)-\left(\mathrm{D}_{1}{ }^{*} \cap \mathrm{D}_{3}{ }^{*}\right)-\left(\mathrm{D}_{2}{ }^{*} \cap \mathrm{D}_{3}{ }^{*}\right)+\left(\mathrm{D}_{1}{ }^{*} \cap \mathrm{D}_{2}{ }^{*} \cap \mathrm{D}_{3}{ }^{*}\right)$
or
(2)

$$
\mathrm{D}_{1}+\mathrm{D}_{2}+\mathrm{D}_{3}-\left(\mathrm{D}_{1}^{*} \cap \mathrm{D}_{2}^{*}\right)-\left(\mathrm{D}_{1}^{*} \cap \mathrm{D}_{3}^{*}\right)-\left(\mathrm{D}_{2}^{*} \cap \mathrm{D}_{3}^{*}\right)-\left(\mathrm{D}_{1}^{*} \cap \mathrm{D}_{2}^{*} \cap \mathrm{D}_{3}^{*}\right)
$$

where $\mathrm{D}_{1} *, \mathrm{D}_{2} *$, and $\mathrm{D}_{3} *$ are rectangular approximations of $\mathrm{I}_{1}, \mathrm{D}_{2}$, and $D_{3}$ respectively.

When we substitute (9.8) into (9.6), we have

$$
\begin{align*}
\mathrm{F} *\left(\mathrm{v}_{1}, \mathrm{v}_{2}, \mathrm{v}_{3}\right)=1-\left[\iint_{\mathrm{D}_{1}^{*}}+\iint_{\mathrm{D}_{2}^{*}}+\right. & \int_{\mathrm{D}_{3}^{*}} \int_{\mathrm{D}_{1}^{*} \cap \mathrm{D}_{2}^{*}}-\int_{\mathrm{D}_{1}^{*} \cap \mathrm{D}_{3}^{*}}-\int_{\mathrm{D}_{2} * \cap \mathrm{D}_{3} *} \int_{\mathrm{D}_{1} * \cap \mathrm{D}_{2} * \cap \mathrm{D}_{3}^{*}}
\end{align*}
$$

where $\iint_{A}$ is a short hand notation for $\iint_{A} f\left(y, y^{\prime}\right) d y d y^{\prime}$.
Now the mechanics of finding the intersection of rectangles can be utilized to handle the last four terms in (9.10). An approximation for the joint c.d.f. of three rectangular coverages is thus obtained.

Since expression (9.8) is equivalent to $D_{1} * \cup D_{2} * \cup D_{3} *$, of which $D_{1} \cup D_{2} \cup D_{3}$ is a subset, we shall have

$$
F^{*}\left(v_{1}, v_{2}, v_{3}\right) \leq F\left(v_{1}, v_{2}, v_{3}\right) .
$$

Unfortunately, this approximation is on the wrong side of the true value.

When we use the second approximation, expressed in (9.9), for $D_{1} \cup D_{2} \cup D_{3}$ in (9.6), the relationship between $F *$ and $F$ is not at all clear. We may have

$$
\begin{aligned}
& F^{*}\left(v_{1}, v_{2}, v_{3}\right) \leq F\left(v_{1}, v_{2}, v_{3}\right), \\
\text { or } \quad & F^{*}\left(v_{1}, v_{2}, v_{3}\right) \geq F\left(v_{1}, v_{2}, v_{3}\right) .
\end{aligned}
$$

Our inclination is to recommend the second approximation since we have
a chance to be on the right side in this approximation. That is

$$
\begin{align*}
\mathrm{F}^{*}\left(\mathrm{v}_{1}, \mathrm{v}_{2}, \mathrm{v}_{3}\right)=1-\left[\iint_{\mathrm{D}_{1}}+\iint_{\mathrm{D}_{2}}+\iint_{\mathrm{D}_{3}}-\int_{\mathrm{D}_{1} * \cap \mathrm{D}_{2}^{*}} \int_{\mathrm{D}_{1}^{*} \cap \mathrm{D}_{3} *}-\int_{\mathrm{D}_{2} * \cap \mathrm{D}_{3}^{*}}\right. & \int_{\mathrm{D}_{1} * \cap \mathrm{D}_{2} * \wedge_{D_{3}} *}
\end{align*}
$$

In the general case of $m$ rectangular targets, the joint c.d.f. of m rectangular coverages is given by

$$
\begin{equation*}
F\left(v_{1}, v_{2}, \ldots, v_{m}\right)=1-\int_{D_{1} \cup D_{2} \cup \ldots D_{m}} f\left(y, y^{\prime}\right) d y d y^{\prime} \tag{9.12}
\end{equation*}
$$

By using the 'Principle of Inclusion and Exclusion", we can always express the union as the sum of intersections; namely

$$
\left.\begin{array}{rl}
D_{1} \cup D_{2} \quad \cdots \cup D_{m}= & \sum_{i=1}^{m} D_{i}-\underset{i<j}{\sum}\left(D_{i} \cap D_{j}\right)
\end{array}\right) \underset{i<j<k}{\sum}\left(D_{i} \cap D_{j} \cap D_{k}\right)-\ldots .
$$

We may use

$$
\begin{aligned}
\sum_{i=1}^{m} D_{i}-\sum_{i<j}^{\sum}\left(D_{i} * \cap D_{j}^{*}\right) & +\sum_{i<j<k}^{\sum}\left(D_{i}^{*} \cap D_{j}^{*} \cap D_{k}^{*}\right)-\ldots \\
& +(-1)^{m+1}\left(D_{1}^{*} \cap D_{2}^{*} \cap \cdots \cap D_{m}^{*}\right)
\end{aligned}
$$

to approximate (9.13) and then substitute it into (9.12) to get $F^{*}\left(v_{1}, v_{2} \ldots v_{m}\right)$.

In the next chapter, we shall have more to say about the possible future studies based on the results obtained in this chapter.

CHAPTER X

## SUMMARY AND POSSIBLE EXTENSIONS

## 1. Summary

The purpose of this study was to find the joint distribution of the coverages on two rectangular targets by one rectangular pattern. Following a natural order of development, we have derived the c.d.f. and the p.d.f. of one linear coverage, the c.d.f. and the p.d.f. of one rectangular coverage, the joint c.d.f. and the joint p.d.f. of two linear coverages, an approximation of the joint c.d.f. of two rectangular coverages. Also, we have found the joint probabilities of some interesting events, e.g., the probability of hitting both targets; missing both targets, etc. A Two-Way Table Method was introduced to find the probabilities of some other interesting events, once the probability of hitting both targets is obtained. A "power up" formula was given to extend the two-way table to $n(n>2)$ identical or non-identical patterns. The question of "the fewest number of passes required to achieve a specified probability of hitting both targets" is investigated, and a formula which can be solved iteratively is given to give the answer to this question.

A way to extend this study to handle the general case of m rectangular targets is outlined in the last chapter. This is possible due to the simple mechanism we developed to find the overlap of m line segments.

## 2. Possible Extensions

One Target Being $\cdot \mathrm{a}$ Subset of
Another Target

A11 through this study, we have assumed the separation of the two targets under consideration. The situation that one target is a subset of another target may arise in the following way. We have a single target, but a small portion of it is the 'heart' of this target. Consequently, we like to treat this portion differently, e.g., we want to have a higher fractional coverage on this portion than on the rest of the target. Figure 29 illustrates this situation:


Figure 29. The Heart Is More Important than the Body

Strictly speaking, we should consider this situation as if we have two targets, with the "heart" being of the shape $\square$ and the "body" being of the shape $\square$. It can be seen immediately that this sort of rigorows treatment will vastly complicate the calculation of almost any joint probability. To avoid this complication, we may approximate the "body" by the whole target. It is in this way that we have two rectangular targets with one being a subset of the other. Of course, this approximation is good only when the 'heart' is a small portion of the target.

Once we have two rectangular targets, we can construct rectangles around them corresponding to the desired joint probability statement and find (or approximate) the probability just like the way we did it all along.

## More about the Case of $m$ Rectangular Targets

The theory and material about the case of $m$ rectangular targets developed in Chapter IX can be explored further. For example, when $m=3$, we can find

Pr (hitting Target 1 and 2 but missing Target 3)

$$
=\int_{K_{1} \cap K_{2}}-\int_{K_{1} \cap K_{2} \cap K_{3}} \int_{K_{1}}
$$

and
$\operatorname{Pr}$ (hitting only two targets)

$$
=\int_{K_{1} \cap K_{2}}+\iint_{K_{1} \cap K_{3}}+\int_{K_{2} \cap K_{3}}-3 \int_{K_{1} \cap K_{2} \cap K_{3}} \int
$$

In this direction, many useful questions can be asked and answered in the general case of $m$ rectangular targets. It is even possible to develop an 'M-way Table Method' analogous to the Two-way Table Method we illustrated in Chapter VII. We leave this to the hands of future researchers in this field.

## To Increase the Number of Patterns

In the context of 'Hitting or Missing', there is no problem in handling the case of $n$ rectangular patterns, as has been demonstrated in Chapter VII, Section 3. But in the general context of the c.d.f., it is very difficult to handle even two linear patterns delivered on one linear target. For one thing, we have the overlap of Pattern 1 and Pattern 2 to worry about. For another, there are uncountably infinite ways that we can combine coverages by Pattern 1 and Pattern 2 to satisfy the event "C su." We believe a different approach other than that developed in this study is needed.

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## APPENDIX

## A NUMERICAL EXAMPLE OF THE JOINT PROBABILITY OF TWO RECTANGULAR COVERAGES

At the end of Chapter VII, we claimed that when the numerical values of the target-pattern configuration are given, it is straightforward but tedious to find the exact joint probability of two rectangular coverages for any specified $v_{1}$ and $v_{2}$ values. In this Appendix we shall illustrate how this can be done in an example.

Let us consider the following configuration of one rectangular pattern being delivered on two rectangular targets:
$\mathrm{L}_{\mathrm{T}_{1}}=$ length of Target 1 in the range direction $=50$
$\mathrm{L}_{\mathrm{T}_{1}}^{\prime}=$ length of Target 1 in the deflection direction $=20$
$\mathrm{L}_{\mathrm{T}_{2}}=$ length of Target 2 in the range direction $=50$
$\mathrm{L}_{\mathrm{T}_{2}}^{\prime}=$ length of Target 2 in the deflection direction $=20$
$\beta_{2}=$ center of Target 2 in the range direction $=0$
$\beta_{2}^{\prime}=$ center of Target 2 in the deflection direction $=35$
$\mathrm{L}_{\mathrm{P}}=$ length of the pattern in the range direction $=70$
$L_{P}^{\prime}=$ length of the pattern in the deflection direction $=40$
$\mathrm{M}=$ aimpoint in the range direction $=0$
$\mathrm{M}^{\prime}=$ aimpoint in the deflection direction $=17.5$

$$
\begin{aligned}
& \sigma=\text { aiming error in the range direction }=20 \\
& \sigma^{\prime}=\text { aiming in the deflection direction }=10 .
\end{aligned}
$$

As usual, we designate the center of Target 1 as the center of the Cartesian coordinate system, $(0,0)$. Now using the definitions in Chapter II, we shall have:

$$
\begin{aligned}
& \mathrm{T}_{1}=1.25 \\
& \mathrm{~T}_{1}^{\prime}=1 \\
& \mathrm{~T}_{2}=1.25 \\
& \mathrm{~T}_{2}^{\prime}=1 \\
& \theta_{2}=0 \\
& \theta_{2}^{\prime}=3.5 \\
& \mathrm{P}^{\prime}=1.75 \\
& \mathrm{P}^{\prime}=2 \\
& \mu^{\prime}=0 \\
& \mu^{\prime}=1.75 .
\end{aligned}
$$

Figure 30, illustrates this situation with all distances standardized by the aiming errors $\sigma$ and $\sigma^{1}$. The standardized areas of Tar= get 1, Target 2, and the pattern are indicated in the bottom of each. They are:

The standardized area of Target $1=2 \mathrm{~T}_{1} \times 2 \mathrm{~T}_{2}=2.5 \times 2=5$,
the standardized area of Target $2=2 \mathrm{~T}_{2} \mid \times 2 \mathrm{~T}_{2}{ }^{\prime}=2.5 \times 2=5$, and


Figure 30. An Example of One Rectangular Pattern Being Delivered on Two Rectangular Targets

We note that in this configuration, two targets are of the same size and their centers line up horizontally. Also the aimpoint is placed midway between the two target centers. We did this in order to simplify the calculation of joint probabilities. In a more general configuration, the joint probabilities can be obtained in a fashion similar to what is done here in this case. The following values will also be needed.

$$
\begin{aligned}
& \mathrm{S}_{1}=\mathrm{T}_{1}+\mathrm{P}=3 \\
& \mathrm{~S}_{1}^{\prime}=\mathrm{T}_{1}^{\prime}+\mathrm{P}^{\prime}=3 \\
& \mathrm{R}_{1}=\left|\mathrm{T}_{1}-\mathrm{P}\right|=0.5 \\
& \mathrm{R}_{1}^{\prime}=\left|\mathrm{T}_{1}^{\prime}-\mathrm{P}^{\prime}\right|=1 \\
& \mathrm{~S}_{2}=\mathrm{T}_{2}+\mathrm{P}=3 \\
& \mathrm{~S}_{2}^{\prime}=\mathrm{T}_{2}^{\prime}+\mathrm{P}^{\prime}=3 \\
& \mathrm{R}_{2}=\left|\mathrm{T}_{2}-\mathrm{P}\right|=0.5 \\
& \mathrm{R}_{2}^{\prime}=\left|\mathrm{T}_{2}^{\prime}-\mathrm{P}^{\prime}\right|=1
\end{aligned}
$$

We shall find the joint probability of "the fractional coverage on Target $1 \geq r_{1}$ and the fractional coverage $\geq r_{2}$ " for $r_{1}=0,1 / 4,2 / 4,3 / 4$, 1 and $r_{2}=0,1 / 4,2 / 4,3 / 4,1$. First, we express the fractional coverage $r$ in terms of a standardized area $v$. That is

$$
\begin{aligned}
& v_{1}=\text { standardized area of Target } 1 \mathrm{xr}_{1}=5 \mathrm{r}_{1} \\
& \mathrm{v}_{2}=\text { standardized area of Target } 2 \mathrm{xr}_{2}=5 \mathrm{r}_{2}
\end{aligned}
$$

(Recall that the standardized area of both Target 1 and Target 2 is 5) From this relationship, we have, for example,

$$
\begin{aligned}
& \operatorname{Pr}(\text { fractional coverage on Target } 1 \geq 1 / 2 \text {, fractional coverage on } \\
& \quad \text { Target } 2 \geq 1 / 4) \\
& =\operatorname{Pr}\left(z_{1} \geq 2.5, z_{2} \geq 1.25\right)
\end{aligned}
$$

Thus, the problem becomes to find $\operatorname{Pr}\left(z_{1} \geq v_{1}, z_{2} \geq v_{2}\right)$ for $v_{1}=0,1.25$, $2.5,3.75,5$ and $v_{2}=0,1.25,2.5,3.75,5$.

Some joint probabilities can be found straightforwardly. For example,

$$
\begin{align*}
& \operatorname{Pr}\left(z_{1} \geq 0, z_{2} \geq 0\right)=1 \\
& \operatorname{Pr}\left(z_{1} \geq 0, z_{2} \geq 2.5\right)=\operatorname{Pr}\left(z_{2} \geq 2.5\right)=1-F_{z_{2}}(2.5) \tag{A1}
\end{align*}
$$

The last equation in (Al) is true since $\operatorname{Pr}\left(Z_{2}=2.5\right)=0$. The value of $F_{Z_{2}}(2.5)$ can be obtained by using expression (3.3) directly.

Some of the joint probabilities are found by integrating $f\left(y, y^{\prime}\right)$ over the region $D_{1} \cap D_{2}$. It is this region that we have to graph carefully and partition it before doing the numerical integration. Consider the $\operatorname{Pr}\left(z_{1} \geq 1.25, z_{2} \geq 3.75\right)$, for example. Corresponding to the event $z_{1} \geq 1.25$, we can construct a $D_{1}$ region around the center of Target 1. Corresponding to the event $z_{2} \geq 3.75$, we can also construct a $D_{2}$ region around the center of Target 2 . The boundaries of $D_{1}$ and $D_{2}$ are well defined in Figure 13. Figure 31 shows both $D_{1}$ and $D_{2}$ and the way they intersect. Because of the symmetry, we only have to consider the upper half of $D_{1} \cap D_{2}$ : We partition it into two areas, Area 1 and Area 2 as shown in Figure 31.

The equation representing the curve on the upper right corner of the $D_{1}$ region is, by the defintion in Figure 13,

$$
\begin{equation*}
\left|y-\theta_{1}\right| \cdot\left|y^{\prime}-\theta_{1}\right|-S_{1}^{\prime}| | y-\theta_{1}\left|-S_{1}^{\prime}\right| y^{\prime}-\theta_{1}{ }^{\prime} \mid+S_{1} \cdot S_{1}{ }^{\prime}=v_{1} \tag{2}
\end{equation*}
$$

Substituting ${ }_{1}=\theta_{1}^{\prime}=0, S_{1}=3, S_{1}^{\prime}=3$, and $v_{1}=1.25$ into (A2), we obtain:

$$
y=\frac{3 y^{\prime}-7.75}{y^{\prime}-3}
$$

Similarly, we can obtain the equation representing the curve on the left upper corner of the $D_{2}$ region:

$$
y=\frac{3 y^{\prime}-5.25}{y^{\prime}-0.5}
$$



Figure 31. A Numerical Example of $D_{1} \cap D_{2}$

We can now see that

$$
\begin{align*}
& \operatorname{Pr}\left(z_{1} \geq 1.25, z_{2} \geq 3.75\right)=\int_{D_{1} \cap} \int_{D_{2}} f\left(y, y^{\prime}\right) d y d y^{\prime} \\
= & 2\left\{\int_{\text {Area }} f\left(y, y^{\prime}\right) d y d y^{\prime}+\int_{\text {Area }} \int_{2} f\left(y, y^{\prime}\right) d y d y^{\prime}\right\} \\
= & \int_{0}^{2.375} \frac{3 y^{\prime}-5.25}{y^{\prime}-0.5} g(y) g\left(y^{\prime}-1.75\right) d y d y^{\prime} \\
& \left.\int_{2}^{2.375} \int_{0}^{2.5} \frac{3 y^{\prime}-7.75}{y^{\prime}-3} g(y) g\left(y^{\prime}-1.75\right) d y d y^{\prime}\right\} \\
& +\int_{\left.2.5\left(\frac{3 y^{\prime}-5.25}{y^{\prime}-0.5}\right)-G(0)\right] g\left(y^{\prime}-1.75\right) d y^{\prime}}^{2.375}\left[\begin{array}{ll}
\left.\left[G\left(\frac{3 y^{\prime}-7.75}{y^{\prime}-3}\right)-G(0)\right] g\left(y^{\prime}-1.75\right) d y^{\prime}\right\}
\end{array}\right.
\end{align*}
$$

Two numerical integrations are needed to find the values in expression (A3), which turns out to be 0.096 . This is a way to find $\operatorname{Pr}\left(z_{1} \geq 1.25, z_{2} \geq 3.75\right)$, which is $\operatorname{Pr}$ (fractional coverage on Target $1 \geq 1 / 4$, fractional coverage on Target $2 \geq 3 / 4$.

If we use rectangles $D_{1} *$ and $D_{2}^{*}$ to approximate $D_{1}$ and $D_{2}$, then the approximated joint probability is:

$$
\begin{aligned}
\operatorname{Pr} & \left(z_{1} \geq 1.25, z_{2} \geq 3.75\right)=\int_{D_{1}^{*} \bigcap_{D_{2}}} \int_{-1.125} f\left(y, y^{\prime}\right) d y d y^{\prime} \\
& =\int_{2}^{1.125} g(y) d y \cdot \int_{2}^{2.5} g\left(y^{\prime}-1.75\right) d y^{\prime} \\
& =[G(1.125)-G(-1.125)] \cdot[G(0.75)-G(0.25)] \\
& =0.129 .
\end{aligned}
$$

In this fashion, we have found both the exact and the approximated joint probabilities of "fractional coverage on Target $1 \geq r_{1}$ and fractional coverage $\geq r_{2}$ " for $r_{1}=0,1 / 4,2 / 4,3 / 4,1$ and $r_{2}=0,1 / 4,4 / 4$, $3 / 4,1$. TABLE II give the exact joint probabilities. FC1 in the table stands for "the fractional coverage on Target 1", and FC2 in the table stands for 'the fractional coverage on Target 2." TABLE III give the approximated joint probabilities. AFC1 and AFC2 have the same meaning as FC1 and FC2 except the extra "A" stands for "approximated."

TABLE II
THE EXACT JOINT PROBABILITY OF TWO FRACTIONAL COVERAGES

|  | 1 | 0.086 | 0.0 | 0.0 | 0.0 |
| :--- | :--- | :--- | :--- | :--- | :--- |
| $\geq 3 / 4$ | 0.269 | 0.096 | 0.0 | 0.0 | 0.0 |
| $\geq 2 / 4$ | 0.491 | 0.262 | 0.109 | 0.0 | 0.0 |
| $\geq 1 / 4$ | 0.717 | 0.457 | 0.262 | 0.096 | 0.0 |
| $\geq 0$ | 1.000 | 0.717 | 0.491 | 0.269 | 0.086 |

TABLE III
THE APPROXIMATED JOINT PROBABILITY OF TWO FRACTIONAL COVERAGES

| $\geq 1$ | 0.086 | 0.0 | 0.0 | 0.0 | 0.0 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| $\geq 3 / 4$ | 0.269 | 0.129 | 0.0 | 0.0 | 0.0 |
| $\geq 2 / 4$ | 0.491 | 0.342 | 0.182 | 0.0 | 0.0 |
| $\geq 1 / 4$ | 0.717 | 0.537 | 0.342 | 0.129 | 0.0 |
| $\geq 0$ | 1.000 | 0.717 | 0.491 | 0.269 | 0.086 |
| AFC2 | $\geq 0$ | $\geq 1 / 4$ | $\geq 2 / 4$ | $\geq 3 / 4$ | $\geq 1$ |

VITA<br>Pao-liang Chen<br>Candidate for the Degree of<br>Doctor of Philosophy

Thesis: ON THE JOINT DISTRIBUTION OF COVERAGES
Major Field: Statistics
Biographical:
Personal Data: Born in Shanghai, China, November 28, 1943, the son of Mr. and Mrs. Siang-Kang Chen.

Education: Graduated from Ti-tong High School, Taipei, Taiwan, in June, 1960; received the Bachelor of Arts degree in Chinese Literature from National Cheng-chi University, Taipie, Taiwan, in June, 1965; received the Master of Science degree in Statistics from San Diego State University, San Diego, California, in July, 1973; completed the requirements for the Degree of Doctor of Philosophy at Oklahoma State University, Stillwater, Oklahoma, in July, 1976.

Professional Experience: Chinese and History Instructor at Wen-shen Middle School, Taipei, Taiwan, 1966-1968; graduate teaching assistant at San Diego State University, San Diego, California, 1970-1973; graduate teaching assistant at Oklahoma State University, Stillwater, Oklahoma, 1973-1974; graduate research assistant at the same institution, 1974-1976; member of the American Statistical Association.

Published Report: 'Expected Fractional Coverage and Expected Overall Damage in Multiple Pass Situations", with David L. Weeks and William L. Gay (August, 1975).


[^0]:    * To make the reference easy, we shall sometimes refer to "the coverage on one linear target by one linear pattern" simply as "one linear coverage." Similarly, "the coverage on two linear targets by one linear pattern" is referred to as "two linear coverages", and "the coverage on one rectangular coverage by one rectangular pattern" as 'one rectangular coverage", etc.

[^1]:    * See, for example, Ash (1970, p. 59)

[^2]:    * n patterns are identical if they have same size, same aim point, and same aiming errors.

